Location Estimation in Smart Homes Settings with RFID Systems

Belal Alsinglawi

A thesis submitted in fulfilment for the degree of

Master of Science (Honours)

Western Sydney University

School of Computing, Engineering and Mathematics

Supervisors: **Dr. Quang Vinh Nguyen**
Dr. Upul Gunawardana
Prof. Anthony Maeder
Prof. Simeon Simoff

January 2017

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Indoor localisation technologies are a core component of Smart Homes. Many applications within Smart Homes benefit from localisation technologies to determine the locations of things, objects and people. The tremendous characteristics of the Radio Frequency Identification (RFID) systems have become one of the enabler technologies in the Internet of Things (IOT) that connect objects and things wirelessly. RFID is a promising technology in indoor positioning that not only uniquely identifies entities but also locates affixed RFID tags on objects or subjects in stationary and real-time. The rapid advancement in RFID-based systems has sparked the interest of researchers in Smart Homes to employ RFID technologies and potentials to assist with optimising (non-) pervasive healthcare systems in automated homes.

In this research localisation techniques and enabled positioning sensors are investigated. Passive RFID sensors are used to localise passive tags that are affixed to Smart Home objects and track the movement of individuals in stationary and real-time settings. In this study, we develop an affordable passive localisation platform using inexpensive passive RFID sensors. To fillful this aim, a passive localisation framework using minimum tracking resources (RFID sensors) has been designed. A localisation prototype and localisation application that examined the affixed RFID tag on objects to evaluate our proposed locaisation framework was then developed. Localising algorithms were utilised to achieve enhanced accuracy of localising one particular passive tag which that affixed to target objects.

This thesis uses a general enough approach so that it could be applied more widely to other applications in addition to Health Smart Homes. A passive RFID localising framework is designed and developed through systematic procedures. A localising platform is built to test the proposed framework, along with developing a RFID tracking application using Java programming language and further data analysis in MATLAB. This project applies localisation procedures and evaluates them experimentally. The experimental study positively confirms that our proposed localisation framework is capable of enhancing the accuracy of the location of the tracked individual. The low-cost design uses only one passive RFID target tag, one RFID reader and three to four antennas.

DEDICATION

I dedicate this work to my parents for always supporting me in my study and my life. Also, I dedicate it to my family members for their continuous help and assistance.

ACKNOWLEDGEMENT

First of all, I feel my proud and privileged to express my deep, sincere gratitude and indebtedness to my Advisor Dr Quang Vinh Nguyen of Computing, Mathematics and Engineering, Western Sydney University, for all of the support and the encouragement he gave me. His office was always open for me whenever I wanted help for my research. His guidance, motivation and countless advices steered me in the right the direction whenever he thought I needed it during my academic journey. It is a great honour to work under his supervision

I would express my deepest thanks and sincere appreciation to Dr Upul Gunawardana, Professor Anthony Maeder and Professor Simeon Simoff of Computing, Mathematics and Engineering, Western Sydney University, for their valuable suggestions and comprehensive advice during my study. Furthermore, I would like to thank the students who participated in this project and their kind support, especially to Tony Liu for his passionate participation and effort.

Statement

I certify that the work in this thesis is to my best knowledge and belief except as acknowledged in this thesis. I hereby confirm that the thesis has not been submitted anywhere else for any either in whole or in part, for any degree at any institution.

[redacted]

LIST OF ABBREVIATIONS

ADL	Activities of Daily Living
AOA	Angle of Arrival
BADL	Basic Activities of Daily Living
GMM	Gaussian Mixture Model
GPS	Global Positioning System
HMM	Hidden Markov Model
IADL	Instrumental Activities of Daily Living
IPS	Indoor Positioning Systems
IR	Infrared
kNN	k-Nearest Neighbours algorithm
LOS	Line of Sight
NLOS	Non–Line–of–Sight
PDOA	Phase Difference of Arrival
POA	Phase of angle
RF	Radio Frequency
RFID	Radio Frequency Identification
RSS	Received signal strength
RSSI	Received Signal Strength Indication
SH	Smart Homes

SVM	Support Vector Machine
TDOA	Difference of Time Arrival
TOA	Time of Arrival
UHF	Ultra-high Frequency
UWB	Ultra-Wideband
WLAN	Wireless Lan Network
WPAN	Wireless Personal Area Network

1 INTRODUCTION

1.1 Background

Location estimation systems in indoor environments have recently gained popularity in the domain of Smart Homes. Indoor Positioning Systems use wireless communication networks (short-range to long-range) and are one of the main components in Smart Homes. Several technologies within indoor environments have been adapted to different applications such as asset management, healthcare, security, warehouse and people tracking. Technologies such as RFID, Bluetooth, and WiFi are commonly use in Smart Homes. Other technologies like Global Positioning Systems (GPS) are not suitable for indoor tracking due to non-line-of-site issues and the need for communication satellite systems [1].

The principle of locations systems (localisation systems) in Smart Homes relies on sensing the activity performed by individuals and location estimation at a specific time. Localisations systems in Smart Homes are categorised into radio frequency (RF) based technologies, optical sensors, sound waves sensors and electromagnetic field sensors [2]. These technologies are commonly used in Smart Homes to allow subject tracking and object localisation. Radio frequency based systems have gained significant popularity in Smart Home projects in various life applications. Examples of indoor localisation technologies include radio frequency identification (RFID) [3], Bluetooth [4], Zigbee [5] ultra-wide band (UWB) [6], and infrared [7].

RFID based systems have potential to offer a substantial improvement to healthcare delivery, both within the clinical and home environment [8]. A significant trend in Smart Home healthcare has been in aged care and for impaired individuals. Research into Smart Home healthcare and localisation technologies has focused mainly on building technologies and on improving location based systems for a better understanding of human movements and activities within the indoor environment system [9-12]. With previous localisation works and systems that were successfully able to track objects and movement of individuals in indoor environment. Using various technologies with desired characteristics and accuracy resolution of being able to locate people individuals in more than centimetres [13, 14].

1.2 Research limitations

Localisation in Smart Homes based on radio frequency (RF) tracking systems to improve wellbeing has become feasible in the indoor environment. Nevertheless, there are still a number of key issues with these smart technologies which are adapted in indoor environments, including accuracy in the location estimation and affordability of such systems. These challenges need to be improved in order to design, develop and adopt better Smart Home solutions for wellbeing and healthcare applications. This requires further examination of the problems associated with accurate localising of object and individuals location in stationary and real time scenarios to provide a better understanding of the exact nature of the activities that are performed by an individual. Better decisions could then be made to ensure a healthcare monitoring system that monitors and assists individual's healthcare needs in their homes.

1.3 Research Objectives

The primary research objective is to overcome the challenges with Smart Home deployment such as localisation accuracy, tracking stationary objects and moveable subjects. This research uses inexpensive passive RFID positioning sensors to develop¬¬¬ process and accuracy/interference mapping protocol to allow tracking of position and movement of tagged objects and subjects in the Smart Homes. The aims of this thesis are:

1) To develop and investigate a cost-effective Smart Home platform using indoor localisation technologies, such as RFID sensors, that can track tagged objects and subjects movements accurately.
2) To develop a localisation framework using minimum tracking resources to achieve a desirable accuracy.
3) To optimise the accuracy of tracking entities by using appropriate localisation algorithms.
4) To develop an application platform for localisation purposes.

The first aim addresses the affordability challenge of Smart Homes by designing a cost-effective tracking platform using RFID sensing technologies. Development of an appropriate, feasible technique is required to locate tagged objects and subjects in Indoor smart space. The second aim entails development of a localisation based framework that provides high location accuracy using minimal tracking resources and systematic localisation procedures. Testing and examination of the design is needed to validate our proposed module. The third aim is to optimise the accuracy of localising an individual's location. This is achieved by employing the suitable localisation algorithms within the framework. The algorithms should be able to accurately measure the subjects and their interaction with the stationary objects in real-time. In the fourth aim, application programming interface is required to fulfil with above mentioned aims for localisation purposes.

1.4 Thesis Contribution

This thesis makes the following contributions:

1) Provides a comprehensive survey of the Smart Home healthcare using RFID-based systems as well as RFID localisation systems and technologies in Smart Homes settings.
2) Proposes a framework for indoor RFID location systems using passive RFID sensors to localise objects and subjects in the Smart Home environment
3) Develops a calibration process for passive RFID sensors to reduce the interference caused by ambient noise in RFID signals. Extensive experiments and measurements were carried out in the laboratory using passive RFID tags.
4) Implements a low-cost tracking system that uses three to four RFID antennas and a single passive RFID tag.
5) Develops a localisation platform and enabling algorithms to determine the location of an individual in real time.
6) Provides an analysis on the mapping accuracy of various anticipated localisation methods in the proposed localisation platform.

1.5 Thesis Outline

The remainder of this thesis is organised as follows.

Chapter 2 presents and discusses related work in Smart Homes and Smart Homes systems in healthcare, including projects, techniques, technologies, and backgrounds of RFID system challenges. It also covers a broad range of research topics related to RFID and indoor location based systems, as well as discussing the challenges of current RFID systems with a comprehensive table to compare various RFID solutions.

Chapter 3 is divided into two parts. The first section presents the experimental setup of our localisation platform using passive RFID technologies while the second introduces the localisation framework using passive RFID tags for stationary and real-time tracking.

Chapter 4 provides the details of the implementation of the passive RFID localisation. Real experiments were developed and carried out in a laboratory environment where we evaluated the collected data from the system. A discussion is also provided exploring the main findings and key results of the experiments.

Chapter 5 concludes this thesis, providing discussion on the overall findings from the experiments. This chapter shows the benefit of our approach in Smart Homes as well as other potential areas of future work.

2. RELATED WORK

This chapter reviews existing literature on prior work related to the Smart Homes concept, Smart Homes in healthcare and the challenges associated with core Smart Homes systems and challenges in Smart Homes healthcare domain. This chapter also reviews current tracking technologies in Smart Homes, including RFID localisation based systems, RFID algorithms and challenges of the RFID-based system. Finally, it presents research gaps within the field which are required for successful daily living within Smart Homes.

2.1 Smart Home

The Smart Homes concept is formally defined as places of residence that are outfitted with computers and technological devices. The aim of Smart Homes is to provide not only comfort, convenience and a safe environment for occupants but also improvements to the technology which can provide assistance to occupants on a daily basis and help connect them to the outer world [9]. Research into Smart Homes has focused on building advanced technological systems. Smart Homes include applications that unobtrusively monitor the elderly via connection sensors, and that can warn them or healthcare providers of any abnormal conditions [15].

2.1.1 Smart Home in the Case of Healthcare

Smart Homes for healthcare are designed to assist residents to accomplish their daily living activities and improve the quality of health care using advancements in ambient assisted living technologies [16]. The aim of Smart Homes within the healthcare sector is to provide autonomous support for: i) people living in their own residence, ii) elderly and impaired individuals who live independently and require constant health care, and iii) people who suffer from numerous pathologies and handicaps, such as chronic diseases, that require them to stay at hospital or within a caregiver's home [17]. The technology could potentially improve living quality for elderly people and disabled individuals. Therefore, healthcare Smart Homes can also be understood as being a specialised area of Smart Homes, integrated with sensors and actuators that allow intelligent communication and localisation of inhabitants so as to support their daily activities [17].

The amount of research into Smart Homes related to the healthcare domain has increased significantly since the 1990s. Ubiquitous homes have been studied by several researchers who have proposed promising contributions in healthcare and to supporting impaired individuals. Chan et al. [18] reviewed other relevant aspects of Smart Homes (SH) such as human activity recognition and efficiency of implemented sensor systems. The authors argued that Smart Homes are one of the favourable, cost-effective solutions for home care for the elderly and disabled people.

2.1.2 Smart Homes Projects in Healthcare

Several later research projects utilised Smart Home solutions to benefit impaired individuals, the elderly people and patients who required continuous health care support. These projects are summarised in Table 1.

Table 1. Smart Homes for healthcare projects

Project	**Target**	**Description**
Ageing In Place [19]	Impaired elders	Early illness detection
CASAS [20]	Residents daily activities	Home automation and pattern discovery
MavHome [21]	Home inhabitant	Rational agent, inhabitant action prediction
TREVA [22]	Subject (elderly) Smart homes	Wellness status monitoring system
ENABLE [23]	People with dementia	Assistive technology for dementia patients
Smart House [24]	Older people	Lifestyle monitoring, detection of panic alarms
Ubiquitous Home [25]	Living family members	Home context-aware service, real life data collection
Intelligent Sweet Home [26]	Home inhabitant	Intelligent, interaction and interface system (hand gesture recognition)
Welfare Techno Houses [27]	Human behaviour	Monitoring human behaviour in daily life
SPHERE [28]	Ageing people with chronic health conditions	Managed people/elders care and well-being of home environment

Researchers at the University of Missouri, USA, developed a cost-effective project called “Ageing in Place” to assist seniors when living independently at home [19]. The *CASAS* [20] project at the University of Washington aimed to detect activity patterns using data mining techniques. It also created an automation of policies that helped understand changes in activity patterns. The University of Texas, Arlington, introduced the *MavHome* Smart Home project that acted as a rational agent to maximise an inhabitant's living conditions and minimise operational costs [21]. The Smart Condo at the University of Alberta, Canada [29] was a simulated Smart Home that integrated intelligent technologies such as wireless sensors to assist in remote monitoring, improving the quality of living for chronically ill patients and reducing the time spent in hospital.

Several smart home projects have been introduced in ambient assisted living situations in Europe. Gloucester's Smart House [24], a community contribution project, targeted the problems associated with increases of demographic changes of the elderly people throughout the Telecare system, and was based on lifestyle monitoring. SPHERE [28] by the University of Bristol in the UK aimed to help people suffering from chronic health conditions by predicting falls and strokes and by detecting periods of depression or anxiety using computer-based therapy as well as by analysing human eating behaviour. Another project named, *TREVA* [22], was a Smart Homes station that monitored long-term physiological and psychosocial variables. The station helped study the well-being of individuals, including the slow development and deterioration and their vital signs such as; beat-to-beat RR intervals, activity levels and blood pressure. *PROSAFE* [30] aimed to target long-term care and was used as a multi-sensor to continuously monitor elderly people including mobility changes and signs of activity, and sent an alarm in the case of an emergency.

Other notable works in Europe are presented at [23], [31] and [32]. Enable project [23] aimed to provide assistive technologies designed to increase independent living for people with dementia. Devices were installed to assist the patients without technical supporters. *PAMAP* [31] was an Information Communication Technology (ICT) based system that targeted the daily physical activity of elderly individuals in clinical environments. Similar projects such as (*HMFM*, *HOPE* and *HERA* [32]) were innovative ICT service systems focused on ambient assisted living and cost-effective solutions.

In Asia, many smart home projects have been the subject of research. In Japan, the Ministry of International Trade and Industry developed a series of 13 research examples for a project called "Welfare Techno Houses" [27]. This project monitored human behaviour on a daily basis with the aim of improving the quality of both mental and physical health using a combination of infrared and magnetic positioning sensors. Ubiquitous Home [25] was a home context-aware service designed to support seniors in real life scenario to help them live independently in their own homes. It integrated devices and sensors with existing data network infrastructure. Another project, the Intelligent Sweet Home, was introduced to provide an easy living environment for the inhabitants by giving the subjects the freedom of movement using hand gesture recognition [26].

In Australia, Celler et al. [33] proposed a system that showed the interaction between participants and their environments while examining the health status of elderly participants by monitoring their activity remotely within a Smart Homes. Researchers also introduced a smart home model that helped the elderly people and supported their needs based on simple approaches using a hidden semi-Markov [34].

2.1.3 Healthcare Challenges in Smart Homes

Smart Homes have become a feasible and cost-effective aid to assist impaired individuals to live independently. Nevertheless, there are major issues to overcome with smart technologies as in the following:

2.1.3.1 Affordability

Affordability in Smart Homes is still a hard task to achieve. Smart Homes could be designed in order to minimise the installation costs of various components by using existing infrastructure (e.g. Wi-Fi network devices) and examine technologies that could be adapted to a new system [35]. Better designed Smart Home devices, such as sensors, system components, system tools and applications could also reduce the computational time and minimise the cost of implementing the system [36].

2.1.3.2 Reliability

Reliability and usability are important issues to determine whether or not a solution is applicable for Smart Homes in healthcare. Demiris [37] revealed that there were significant reliability and user-friendly concerns when using smart home technologies in residential homes. For example, devices and technologies need to be more user-friendly so that elderly people can use them regularly without difficulty. Further, adequate training for elderly users is crucial, and systems should not obstruct a user's movements or daily activities. Smart Homes will also help patients and older residents in emergency situations, by analysing their daily life patterns, physical movements and by reliably monitoring physiological parameters such as blood pressure [18].

2.1.3.3 Ethical and legal

Privacy is a crucial element when building or adapting Smart Homes. Technologies such as sensors and cameras could lead to privacy issues due to the constant surveillance and monitoring required. Consequently, these technologies are less likely to be a feasible solution. Unfortunately, there is still limited regulation on the patients' rights to protect them from malpractice related issues [18, 38].

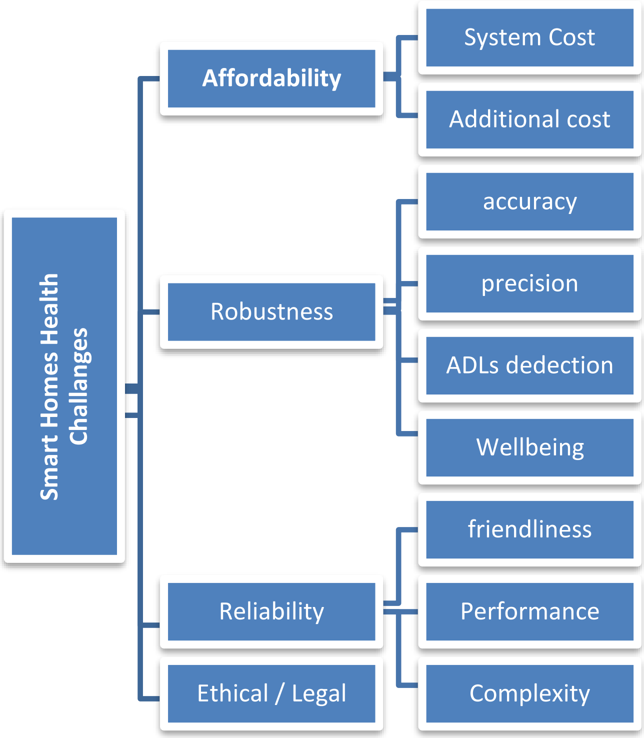

Figure 2.1. Taxonomy of challenges in Smart Home health in indoor environments

2.2 Tracking Technologies in Smart Home

Researchers have recently attempted to find an optimal solution that locates and tracks objects in real time. This would help residents localise and position home objects in indoor environments which assist impaired individuals and elders. Numerous radio frequency technologies for indoor localisation have been investigated such as camera sensors, WLAN [39], Zigbee [5], Ultrasound [40], UWB [41], Bluetooth, Infrared [39] and RFID [39]. Among them, RFID is one of the more promising and robust technologies, and it has been applied in several projects for indoor localisation. It’s benefits are due to the low cost and high reliability for indoor environments.

Table 2 summarises the existing RF technologies for indoor localisation. Further, it compares the average accuracy range of RF technologies along with Frequency range and common measurement method are used in indoor localisation. The accuracy range it various from technology to other and it depends on the communication feature of each technology such as Frequency range and the measuring algorithms that used on each one.

Table 2. A summary of Radio Frequency based systems.

Technology	**Accuracy Range**	**Frequency Range**	**Measuring Method**
RFID	dm – m	30 kHz – 500 kHz (LF) 3 MHz – 30 MHz (HF) 433 MHz / 868 MHz – 930 MHz (UHF) 2.4 GHz – 5.8 GHz (SHF) [42]	Scene Analysis (Fingerprinting), Proximity detection, Triangulation, RSSI
WLAN	m	IEEE 802.11x Standard	RSSI, (Fingerprinting) [43]
Zigbee	m	IEEE 802.15 Standard	RSSI
Bluetooth	cm-m	IEEE 802.15 Standard	RSSI
UWB	cm	3.1 GHz-10.6 GHz [42]	Triangulation TOA, TDOA, Angulation AOA

2.2.1 Radio-Frequency Based Technologies

2.2.1.1 Radio Frequency Identification

RFID is a new, promising technology. It has been exploited in the last decade by several researchers in the field of Smart Homes dealing with finding auspicious indoor positioning solutions for healthcare facilities [9, 44-46].

RFID technology enables the tracking of individuals and objects automatically and independently within an indoor environment, based on the RFID communication model and via radio waves (between readers and tags). It works by sending and receiving the unique identity of persons and objects wirelessly using radio waves. A RFID system consists of readers, tags and a data collection module as seen in Figure 2.2. The readers can either be static or mobile and there are two methods for tracking. In the first method, the reader can be installed in a static location inside the household (such as a wall, a table or a kitchen) to sense the movement of RFID tags. The reader then searches for the tags which are either attached to objects or carried by the person. In the second method, the portable reader detects the static tags in certain positions while the RFID reader can be carried by individuals [47, 48].

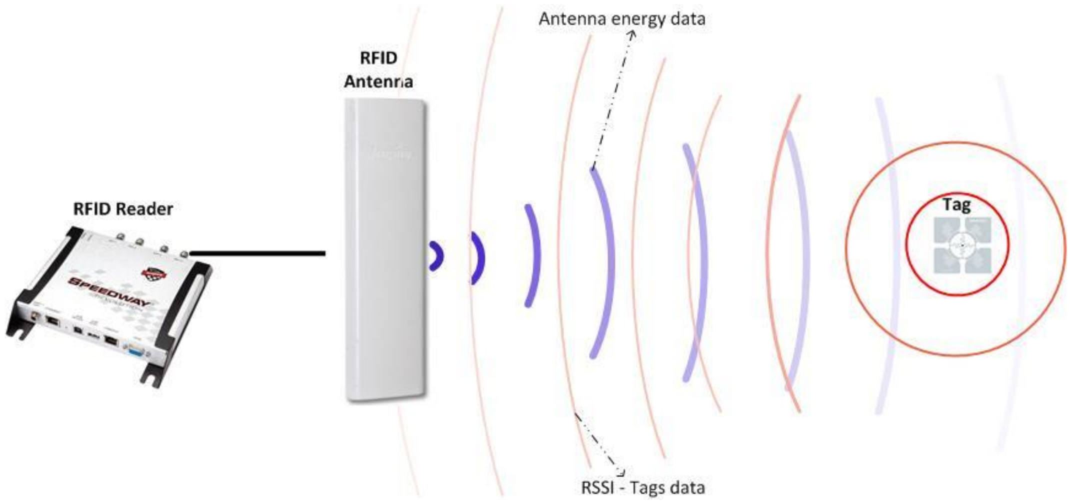

Figure 2.2. Working principles of UHF RFID object-based systems

There are three main categories of RFID tags including active, semi and passive. Active RFID tags have an internal battery to continuously power the device. Of all three types of tags, active has the greatest range [48]. However, active tags have limited lifespans and they rely on energy stored in the internal batteries. Maintenance levels and the degree of intrusiveness for active tags are higher than for their passive counterparts as are the price of the tags and maintenance costs. Semi RFID tags also have an internal battery to power the internal circuits [48]. Semi RFID does not add radio noise and have longer reading range with a memory to store more data. Nevertheless, because it has battery which is larger size, quite expensive, limited battery life

Passive RFID tags have no internal battery. They are smaller in size and are much cheaper than active or semi-active tags. Notably, passive RFID tags are powered by the radio waves that are emitted by the antennas, so they do not require an internal source of power. The tags are usually affixed to objects in Smart Homes, such as cups, kettles or furniture [49].

2.2.1.2 Wi-Fi (WLAN) localisation system

WLAN (Wireless Local Area Networks, IEEE 802.11 standard) or Wi-Fi has become one of the most conventional technologies deployed for indoor positioning and is widely available for home and industrial applications. Several researchers applied WLAN to find effective solutions for indoor positioning for healthcare needs [50].

WLAN's indoor positioning solutions are available as commercial products that use received signal strength indicator (RSSI) based on a fingerprint sensing technique. Some systems also use other positioning methods such as time of arrival (TOA) [51] and angle of arrival (AOA) [52]. RADAR [53] is the first system that uses Wi-Fi for indoor positioning. The accuracy of the RADAR positioning approach has been improved by later research that achieves on average 2m-3m of accuracy[52].

WLAN offers several advantages for healthcare and for the localisation of objects in Smart Homes. Firstly, it is extremely cost efficient as it uses existing infrastructure by connecting with a location server within the coverage area and requires no additional hardware installation [54]. Further, WLAN provides scalable aspects for localisation in indoor environments. For these reasons, WLAN has become one of the effective solutions for commercial uses and residential indoor environments [55]. There is , however, a drawback when using this technology - a multipath occurs due to the physical interaction between individuals and physical objects and the signal strength may change according to the assigned time. Also, the signal may interfere with other appliances on a 2.4GHz ISM band [54].

2.2.1.3 Ultra-wideband

UWB is a technology for both short and high range bandwidth communication. UWB uses RF pulses to communicate between transmitters and receivers. Because can operate by non-line-of-sight (NLOS), UWB has gained popularity as a suitable option for inside-building localisation and aware applications [48, 56]. UWB achieves a higher localisation accuracy (20 to 30 cm) compared to other RF technologies and offers strong multipath resistance. The Ubisense system [39] is an unidirectional UWB location platform, which provides a real-time tracking solution for indoor positioning. The tags emit UWB signals via a network using localisation techniques such as time difference of arrival (TDOA) and angle of arrival (AOA). However, UWB technology is expensive, and is only really suitable for being deployed in large-scale indoor applications.

2.2.1.4 Bluetooth

Bluetooth (IEEE 802.15) is a standard WPAN specification. Bluetooth devices run on a 2.4 GHz ISM band, and most modern mobile devices have a Bluetooth feature. There are several benefits of using Bluetooth tags for indoor usage such as the low cost, higher security (it requires authentication), low power consumption and its small size. Morevoer, each Bluetooth device has a unique identification.

BLIP [4] and Topaz [39] are popular projects that applied Bluetooth technology for indoor location tracking. The accuracy of the Bluetooth systems is within the range of 10m to 15m depending on the positioning techniques (such as RSSI or fingerprint) and other algorithms. The disadvantage of these systems is that the Bluetooth devices have to run during the discovery procedure which increases localisation latency (10-30s) and is not suitable for indoor positioning [54].

2.2.1.5 Zigbee

Zigbee [5] is an emerging wireless technology based on IEEE 802.15.4 standard which is a short to medium communication system. It provides various benefits for indoor home localisation such as it being suitable for low power consumption applications and it does not require higher data processing and transformation in a system. The coverage area of the Zigbee system ranges from 20m to 30m [54]. Similar to most of indoor positioning systems, Zigbee uses RSSI as a positioning method. Its accuracy is varied depending on the use of algorithms, such as Chen et al. [57]. Although this technology has some beneficial features for indoor localisation, the positioning accuracy of Zigbee solutions is limited. Other researchers adapted to Indoor Hybrid solutions that combined Zigbee technology for better accuracy.

2.2.2 Hybrid Systems

The idea of combining different indoor positioning systems is to find better localisation solutions by reducing the limitations of each approach. Therefore, hybrid systems could offer supplementary solutions for indoor scenarios. Several researchers have attempted to find optimal solutions using two or more various positioning technologies. Choi et al. [58] merged Ultrasonic with passive RFID to achieve higher accuracy (1 to 3 cm). However, the system was affected by line-of-sight (LOS) issues which are inherant in Ultrasonics. Sample et al. [59] utilised an optical positioning system with passive RFID tags to improve the accuracy. Jukka et al.[60] combined WLAN with passive RFID tags whose solution provided 80% accuracy. The estimated positions in the applied scenarios had low distance errors which were less than 1 meter.

2.2.3 Other Indoor Positioning Systems

Research was also conducted into the use of optical-based navigation technologies for home indoor positioning [42]. Optical localisation is a preferable solution for many operations due to the high accuracy achieved. Some researchers also combined camera solutions with other positioning technologies and RFID systems as a hybrid approach [59]. However, optical localisation technologies had limitations such as high infrastructure cost and ethical issues associated with video capturing.

2.2.3.1 Infrared-based systems

Infrared systems are favourably used for indoor localisation due to their wide availability in many applications. IR systems mostly use the LOS communication mode while transferring data between receivers and transmitters. The benefits of IR indoor based localisation solutions include their lightweight and high accuracy, making them suitable for portable applications. Nonetheless, using IR for indoor localisation has privacy concerns and security issues and requires expensive infrastructure and system maintenance [54].

2.2.3.2 Ultrasound technologies

An ultrasound localisation system works similar to the way a bat communicates with its surroundings - using low-frequency signals. Ultrasound systems have been used for real-time scenarios, such as in a Cricket indoor location system [40]. These systems are inexpensive and provide relatively good accuracy. However, ultrasound technologies have a negative aspect in that interference, such as metal collision, may reflect from the surroundings when transmitting.

2.3 Smart Homes for Healthcare Components Based on RFID Systems

2.3.1 RFID Technology in Smart Home Healthcare

RFID based applications have been succesfully employed in Smart Homes. In the healthcare domain, RFID technology has been adapted by caregivers to reduce the gap for health care progression and improve patient care. RFID systems have tremendous benefits in Smart Home environments, particularly, 1) RFID tags are small and easy to attach to objects such as plates, spoons, kettles and furniture and 2) they are light enough to be worn by individuals. Smart Homes for healthcare can provide facilities and real-time tracking for elders and patients through the use of RFID chips, which can provide a highly accurate location of a patient and allow the collection information for use by health care professionals. RFID technologies are potentially applicable for indoor objects, subject localisation, recognition of activity and user interaction with household objects. It functions by categorising the information from RFID sensors in order to define the nature of a residents daily activities.

RFID technology enables the tracking of individuals and objects in an indoor environment automatically and independently, based on the communication model (between readers and tags). It operates by sending and receiving information about the unique identity of persons and objects wirelessly by radio waves. The readers can be static or mobile, and there are two methods for tracking. In the first method, the reader can be installed in a static location inside the household (such as a wall, a table or the kitchen) to sense the movement of RFID tags. Then the reader searches for the tags which are either attached to objects or carried by the person. In the second method, the portable reader detects the static tags in certain positions while the RFID reader can be carried by individuals [47, 48].

A Smart Homes health based monitoring system with RFID consists of several components that are combined in one context-aware system (see Figure 2.3). Healthcare information unit is responsible for monitoring healthcare system and users activities, keeping healthcare information records in safe database that is accessible by authorised caregiver staff member such as doctor, nurse, etc. RFID is the communication mechanism between the healthcare application and the healthcare information unit. Figure 2.4, represents the architecture of RFID-based Smart Homes healthcare system includes three main layer; sensing layer, middleware layer, and service layer.

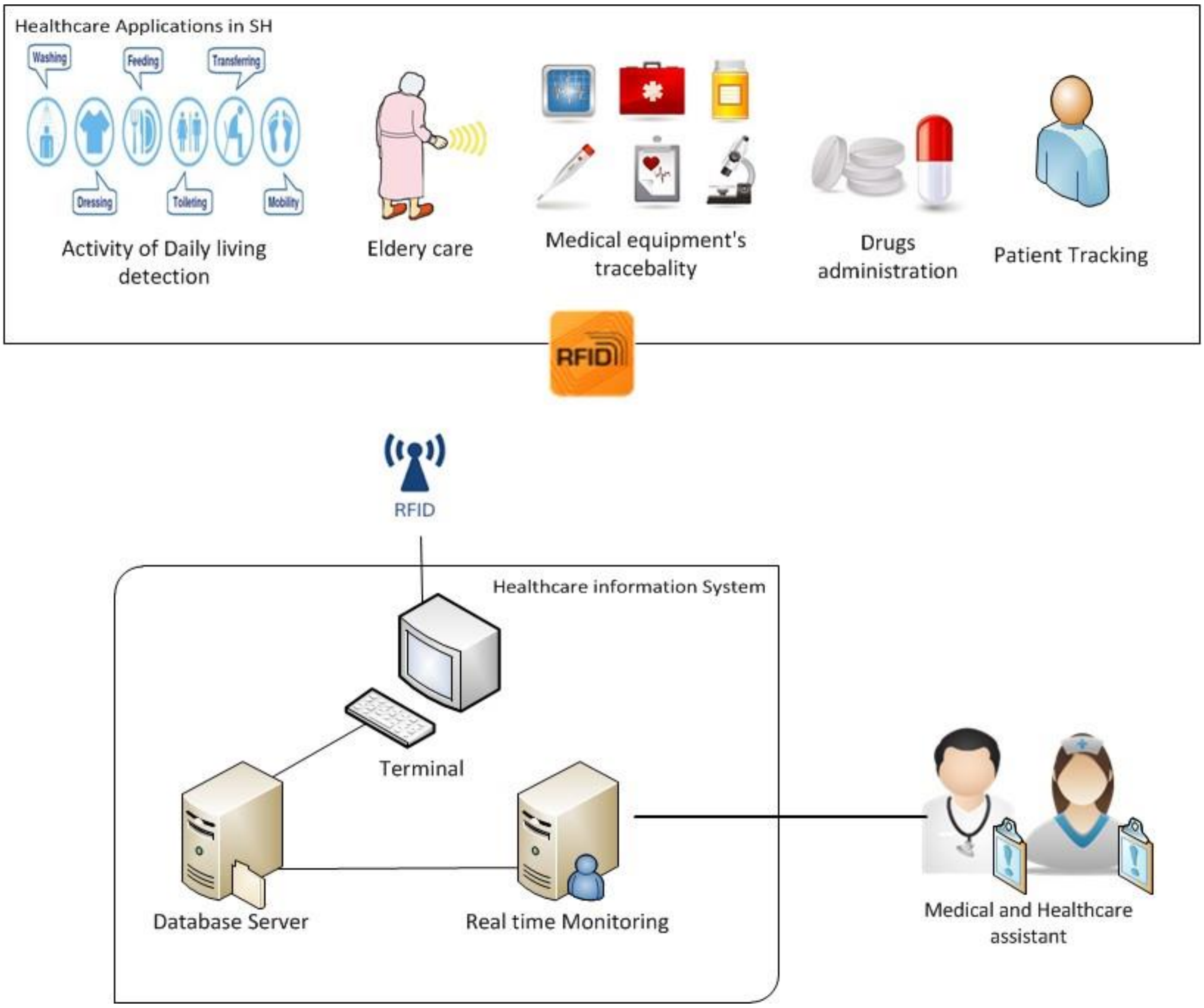

Figure 2.3. Components of RFID System in Smart Home healthcare applications

2.3.2 RFID-Based Perception of Smart Homes for Health

Figure 2.4. RFID-based perception of Smart Homes for health

2.3.2.1 **Sensing *layer***

The sensing layer consists of RFID physical components which are able to sense the movement of targeted objects (e.g. medical equipment). It also captures data from individuals and detects their health status for further processing. The layer collects the information from RFID devices in the test bed from either environmental (e.g. RFID sensors) or wearable sensors (e.g. RFID and accelerometer). RFID Static Environmental Sensors are commercially available with various functionalities. RFID Wearable Sensors can be worn by the participants to measure a person's interactions with home objects and track body movement or detect a fall.

2.3.2.2 Middleware layer

The raw data from the physical layer can be translated to a particular context using inference engines that describe the condition of individuals. Classifiers filter and categorise the data to a particular context such as position and movement of the person [61]. Data reduction and data analysis are also processed in this layer. The software in this layer may combine multiple sensors to intelligibly analyse a data stream [62]. The inference engines are considered to be knowledge representation in the middleware layer and are a main component of the RFID systems [8].

2.3.2.3 Service layer

RFID health information systems in the service layer store information about an individual's health and physical condition (e.g. health database server) which can be accessible by medical staff and caregivers [8] via real time monitoring servers. The context-aware reasoning module assists the end users with their health care needs in various ways such as a notification or warning in case of risks. It also notifies the caregivers about the health of individuals via monitoring and assessment consoles [62]. These consoles help researchers and practitioners to monitor their patients and provide the patients' health status and medical information. The service layer allows the caregivers to interact remotely with the patients and assist them when dealing with abnormal health conditions.

Context-aware systems for healthcare have significantly enhanced the quality of healthcare services and enabled services delivering in healthcare in Smart Homes. It is apparent that RFID-based solutions and studies are improving the advancement in the field.

2.4 Localisation Systems in Smart Homes

Localisation of objects and persons remains a challenging issue in Smart Homes. Researchers have been trying to find inexpensive solutions for tracking objects within the indoor environment using RFID or other locating systems. Some of these studies have used hybrid approaches that provide better localisation yet, add cost and complexity to the systems. Unfortunately, finding affordable solutions to indoor positioning in Smart Homes is an ongoing endeavour.

RADAR [7] by Microsoft is the first RF project applied in an indoor localisation environment. RADAR was dependent on Wi-Fi signal strength or the fingerprinting localisation method. The system achieved accuracy between 2m-5m with 90% precision within 5.9m [7]. It uses WLAN network infrastructure so is easily installed. Nevertheless, the localisation devices have limited energy levels and received signal strength (RSS) as well as privacy concerns [7].

The first noble indoor localisation system that combines ultrasound with RF technologies is used in cricket system [9] and could be used in other various indoor applications such as medical, healthcare and human tracking. The system can achieve high accuracy between 1-3cm for long range tracking with reasonably low cost. However, this system uses battery-powered tags that are not an ideal solution for long running times, whereby the system suffers from an energy consumption issue.

Active Badge [32] is a novel location system proposed by researchers at MIT University. It is aimed at detecting the location of staff members inside the university facilities and provides information about their movements. The active badge is a cost effective solution based on IR sensors which use a small wearable device to transmit infrared radiation every 15 seconds to the sensors through an optical pathway.

Interestingly, Hodges et al. [33] proposed a system that used ultrasonic sensors to determine a location in 3D. The system achieved up to 95% efficiency when reading at 3cm. However, implementation of the sensors was relatively costly.

2.4.1 Metrics and challenges in Indoor Localisation Systems

This section specifies the performance metrics associated with indoor localisation systems with the following criteria:

2.4.1.1 Accuracy

Accuracy is defined as the average Euclidean distance between the estimated location and the actual location [33]. Accuracy in the localisation of individuals in personal monitoring is one of the biggest challenges facing Smart home solutions. Multiple factors affect the accuracy of the results, including 1) the method for determining locations of the subjects in the indoor environment, 2) the size of the testing area and 3) the distance between targeted objects and sensing devices (e.g. sensors and readers). The orientation of sensors also plays a significant role in obtaining better accuracy during the experiments.

2.4.1.2 Coverage

For indoor localisation systems, the coverage parameter can be defined as the spatial extension where system performance should be ensured by indoor positioning [42]. Therefore, in most indoor localisation systems, coverage is a closely related factor to the accuracy of determining the performance of such a system. The coverage is measured in (m), (m^2) or (m^3) [54].

2.4.1.3 Robustness

Finding a means to address accuracy and the robustness of activity recognition is a current pressing issue in the Smart Homes field. At this stage, the infrastructure of Smart Homes must be designed to perform well to interpret several sources of data or distinguish between different sources. If the proposed approach ignored the accuracy factor or the robustness of the activity recognition problem, then unaccountable activities would show up as noise in the data. In most cases, this noise in the data will lower the accuracy and robustness of the system to recognise the activity.

2.4.1.4 Performance

The performance of the Smart Homes system is measured by the success of the system to obtain accurate readings. Some factors affect the localisation processes, such as time delay in calculating the positions of objects or individuals, sudden movements, and environmental changes. Similarly, scalability can influence the performance of the system.

2.4.1.5 Complexity

The complexity of the solution is an important factor when designing Smart Homes. Adding more infrastructure components to the existing solution will result in a more complex system. If a system requires time to locate subjects during localisation and uses a sophisticated algorithm, it is less likely to be adaptable and applicable in daily life scenarios in Smart Homes. Maintenance of such systems is another problem when using a complex solution, as it is ineffective in the long term if the system requires frequent maintenance.

2.4.1.6 Costs

Costs associated with Smart Homes systems include added infrastructure to the existing fixtures, the devices (e.g. positioning devices and system components), installation and maintenance, as well as costs to carry out experiments. For example, WLAN systems have a high relative accuracy that can be used in addition to existing localisation devices. Unfortunately, it costs more when using systems such as WLAN while RFID systems use cheaply available tags [39].

2.4.2 RFID Smart Homes Projects

Early research focused on RFID technology for indoor tracking, but RFID has also been applied to areas such as industrial, medical, automobile and agriculture. RFID technology has been scientifically proven in applications because of its advantages as far as accuracy, cost, efficiency, adaptability, scalability, robustness and simplicity. A comprehensive list of RFID solutions for Smart Homes is discussed in a summaried version in Table 3 and the full version in Table 11 in the Appendix A. The tables compare the common RFID and recent localisation approaches for indoor Smart Homes. The comparison is based on localisation parameters and assessment features that tell us how efficient and robustness each work. For instance, accuracy parameter describes the best precision result achieved in centimetres or meters. This also can be called the margin error of estimated location compared to the actual location of the target entity. Whilst efficiency describes the overall accuracy performance of each system. Technique it can describes the localisation approach that used in each work, and tracking describes type of tracking objects whether it is active, semi active, and passive. Reader, tag and coverage area column it simply demonstrates the deployment area of each system. Last column describes benefits and drawback of each work.

Table 3 provided a compact comparison between common localisation RFID systems in Smart Homes. A comprehensive comparison is presented in Appendix A, Table 11.

Table 3 Short comparison between RFID based localisation solutions in Smart Homes

Solution	Application	Accuracy	Benefits / Drawbacks
LANDMARC [63]	Location awareness	≤ 2m	Cost effective solution. • Less infrastructure required during deployment Minimises the localisation error caused by environmental interference (more precise)
			Complexity and flexibility such as: Long latency. Different tag behaviour during detection (different reading values)
Chawla et al[64]	Indoor localisation (object localisation)	0.18cm	Several algorithms to achieve higher accuracy and efficient solution
			Need to deploy *a* large number of tags for higher accuracy High complexity and installation issues
Athalye, Savic et al. [65]	Location awareness	30cm	New Sense tags which have a dual ability to locate objects
			Battery life issues caused by a comparator that runs whole power circuit.
Bouchard, Fortin-Simard [66]	Indoor tracking (people) / Activities of Daily Living (ADL) detection	≈ 16cm	*Reduced* inaccuracy by applying some localisation filters New mapping protocols
			The system was not tested *on a* large scale with different zones. Lack of real-time tracking for multiple objects.
Bolic et al [67]	Indoor localisation (proximity detection)	32 cm	Inexpensive UHF RFID tags and they are maintenance free
			Requirement of landmark tags for localisation application Relying on semi-passive tags (needs battery changes)

Lionel et al [63] introduced the concept of localisation using tag references in their LANDMARC system which used active tags that were located in fixed positions and measured the distances between readers and tags using a multi-level power method. There were eight levels where Level 1 was the shortest range and eight the longest. The system relied on the received signal to estimate and detect the position of the tags. LANDMARC obtained an accuracy of 1m (50% error distance) with less than 2m in maximum error distance. Work by Zhao et al. [68] used the principles of the LANDMARC system to implement the Virtual Reference Elimination (VIRE) system that located reference tags in a virtual reference tag which enhanced the performance and avoided interference as well as multipath. The authors reported the least error estimation 0.47m within the average of error estimation (0.29m) for non-boundary tags [68] when compared to LANDMARC. Other works also used the LANDMARC concept to enhance the localisation [3, 69]. A solution was presented by Jin et al [3], which improved the overall localisation performance of the former and achieved an accuracy of 72cm using fewer tags around the targets. FLEXER [69] utilised a simulated solution to increase the accuracy where their solutions attained 70cm (or 80%) using applied region mode [69].

Zhang et al [70] implemented RFID diversity elimination algorithm called RFID DeffFree Loc to reduce the mean locating error. In their simulated work, the system obtained an accuracy of 10cm in an environment free of noise, while 19cm was achieved in noisy environments - the accuracy was improved in noisy environments compared to LANDMARC solutions. In contrast, work by Hahnel et al. [71] was one of the first projects that considered indoor localisation and mapping using passive RFID tags, based on a probabilistic measurement model. It applied two antenna readers installed on a mobile robot to detect the static passive RFID tags that were attached to the walls of the tested environment.

Tesoriero et al [53] expressed the idea of turning the area (floor surface) into a grid. A RFID reader attached to a mobile robot sensed the passive RFID tags that were attached in small spaces inside the grid floor. RFID tags were linked to a particular position on a virtual map. The system achieved an accuracy of 0.9m. However, the readers had to be carried during localisation. Work by Bouchard et al. [66] was presented to enhance Fortin-Simard's trilateration model and algorithms [72]. The authors improved the fuzzy localisation using the mean of interface engine and linguistic variables such as likeliness, distance and object detection.

Hekimian-Williams et al. [55] proposed a project that achieved very high and precise localisation results in millimetres using phase difference between two readers. The system used a simple approach that consisted of two readers for locating one active RFID tag. The system, however, always used battery powered tags which required high maintenance and had high associated costs.

Other systems also provided high accuracy in their solutions Vorst [73] applied a Particle Filter (PF) based on a pre-probabilistic approach (self-localisation) to achieve better accuracy while Joho [74], used an antenna orientation and RSSI model. Similarly, Chawla [64] developed several new, linear, binary and parallel search localisation algorithms to enhance the overall accuracy and achieved very good results compared to the previous works with up to 18cm accurate localisation. However, these systems used many tags and more readers which added costs as well as added to the complexity of the system, making them less suitable for indoor environments.

Hybrid methods that combined UWB with RFID were also proposed. Semi-active tags were introduced by D'Errico R. et al [75] where the system used UWB antenna and UHF technology to sense RFID Semi-active tags based on backscattered signals were modelled. The system detected two types of tags 1) dynamic tags based on extended Kalman filters (EKFs) algorithm and 2) static tags using least squares (LS) algorithm. This method achieved relatively high accuracy (20 cm) with less than 0.53m (75%).

Xiong et al. [76] combined WSN and RFID devices as a hybrid approach to achieve desirable results. The authors applied hybrid cooperative positioning algorithms that extended the Kalman filter (EKF) with numerous measurement modules [76]. Their purpose was to find a reliable solution to indoor positioning that was compatible with existing infrastructure from different IPS technology. The method was tested in simulated and experimental environments and achieved considerable levels of accuracy.

Fortin-Simard et al. [72] proposed a method that adopted a new, enhanced trilateration approach using RSSI. They applied various filtering algorithms to reduce the localisation errors that were caused by the interference of environmental surroundings (e.g. metal and walls). The work also reduced the problems generated by the nature of the passive tags and RFID readers during localisation processing. It obtained a high accuracy of 14cm overall. The system was also implemented to support daily life activity recognition.

Sunhong et al. [77] used RFID readers attached to a robot to detect fixed location tags on the floor during robot movement. The work aimed to provide assistance and localisation movement of elders and individuals with disabilities who used motorized wheelchairs. The researchers presented an algorithm to read the speed of the robots movements (or a portable chair), where the accuracy depended on the reading speed against the tag locations. This obtained a promising accuracy of 10cm in comparison to previous similar approaches.

Jachimczyk et al [78] utilised a 3D RFID localisation method using hybrid algorithms in a scene analysis and neural network. The system was tested in three different test cases including active readers, different scenario and cost effectiveness. It performed in both simulated and in real environments to find the optimal configuration for RFID readers. The results were obtained according to some active readers in different scenarios. The scenarios required a certain number of RFID readers to be allocated in each test where it performed according to the number of readers (from 1 to 8). The best condition was achieved when using four or eight readers and the averages of the accuracy were 11cm and 7cm respectively as well as 49cm and 50cm respectively for standard deviation uncertainty.

Athalye et al [65] proposed a solution for indoor localisation by using new semi-active tags called senstags that had dual detection ability. Senstags first detected and decoded backscatter signals from RFID tags (within proximity range) and then communicated with the reader using backscatter modulation as a regular tag. Although this technique achieved good accuracy, it required a long battery life and high system maintenance.

Yang et al [79] introduced some principles for tag distribution localisation and grid patterns. The system defined (SRE) method as the ratio of the number of successful tag readings. This method was successfully applied in detecting multiple RFID passive tags.

Bolic et al [67] presented an approach called Sense-a-Tags (STs) by applying the proximity technique to enhance the passive RFID tags functionality in tracking people and their interaction with objects in real time. The authors tested their STs system in two experiments using a particular number of RFID tags with various tag orientations. The system achieved 32 cm and 48 cm detection accuracy respectively.

2.4.3 Tag- Free Localisation Using RFID-Based Sensors

Several methods have been introduced to address RFID localisation related problems and track within the indoor environment as aforementioned. One of these was a highly desirable method called (Tag-Free localisation).

Tracking using Tag-Free approaches have recently become an active research topic. Many researchers adapted Device-Free localisation using RFID systems due to its feasibility, accuracy and cost-effectiveness compared to previous solutions as mentioned in the literature review. Furthermore, this method does not require subjects to wear tags, especially in the case of tracking an impaired patient such as dementia patients who frequently forget to wear tags or wearable readers. Thus, Tag-Free has become a desirable solution to track moving subjects in Smart Homes.

2.4.3.1 Tag Free RFID Related Work

The Tag-Free passive RFID technique uses RFID tag array for location sensing and route tracking [47]. Work by Ruan et al. [80], introduced a new approach which tracks moving subjects based on classification tasks. They used learning-based classification methods (GMM-based HMM model and kNN-based HMM), to localise subjects from RSSI observed values of RSSI distributions at each grid. Moreover, they introduced a multivariate Gaussian mixture model (kNN and HMM-based) to track moving subjects based on continuous sequences of RSSI.

TASA [47] is a promising hybrid approach that uses inexpensive passive tags with a few RFID active tags located in previously determined positions as reference tags to improve the tracking of moving objects based on both the Tag-Free principle and the RFID array tags. Due to behaviour variations in RFID readers, TASA used group behaviour monitoring in large areas to reduce the noise caused by passive RFID tags. In order to achieve higher accuracy, the authors developed algorithms to reduce the noise in RFID readings and recover trajectories in an online mode. Following, was a work named Twins [81], which implemented a novel cost-effective solution of motion detection using Device-Free Passive RFID tags. The authors implemented two adjacent tags to enhance object localisation thereby achieving an error location of 0.75m, compared to TASA and LANDMARC.

Table 4. Comparison between tag free RFID-based localisation solution

Solution	**Application**	**Method /algorithms**	**Benefits**
TASA [47]	Location sensing	Reference Tags (active & passive tags)	Reduces the noise in passive RFID tags (optimises the accuracy)
Twins [81]	Object localisation in warehousing	kNN & Particle filter	Able to track multiple objects
TagTrack [80]	Track Subjects (Real time)	• kNN-based Hidden Makov Model • Multivariate Gaussian Mixture Model & Hidden Makov Model (GMM-based HMM) • SVM	Optimises the accuracy in tracking moving subjects using learning-based classification
Wagner et al [82]	Location sensing / Imaging based Localisation	Clustering Module	Increases measurement speed and localisation precision

2.5 RFID Tracking Techniques in Smart Homes

Several detection methods have been proposed in the literature for RFID indoor localisation. There are three main detection techniques and position estimations for RFID technology including *Triangulations* (distance estimation), *Scene Analysis* and *Proximity*.

2.5.1 Geometrical Time-based Algorithms

2.5.1.1 Triangulations

This technique relies on the geometrical properties [54] of triangles to determine the target locations. In triangulations, there are two main methods including *lateration* and *time-based*.

- Lateration, trilateration and multilateration techniques estimate the position of an object, where RFID tags were attached, by measuring its distance from multiple reference points (either RFID objects or RFID antenna). This technique is usually called the range measurement technique [39].
- Time-based methods such as TOA and TDOA are techniques which measure the positions of RFID tags (or objects) based on distance measurements [39]. RSS is based on the received signal phase method and phase of arrival based techniques such as Phase Difference of Arrival (PDOA) [54].

Many researchers have investigated RFID localisations using the lateration triangulations on various models for indoor positioning such as those in TOA [83], TDOA [84], PDOA [85] and RSS [86] [74]. Localisation, along with RFID lateration techniques have been used for various indoor positioning applications. However, there are some drawbacks such as multipath (TOA, TDOA) and non-LOS (TOA, TDOA and PDOA).

2.5.1.2 Angulation

The *Angulation* technique, AOA, is defined as the angle between the propagation directions of the incident waves and references, called orientation. The orientation is defined as the fixed direction against which AOA is measured [87]. In this approach, the location is determined in 2-D by calculating the intersection between two beacons, or two positions as measuring elements [40]. AOA requires two beacons to improve the accuracy and needs more than three angles for triangulation. However, AOA is affected by multipath, NLOS propagation and wall reflection, which causes errors for indoor location estimation [54].

2.5.2 Scene Analysis

The scene analysis method first collects the features (fingerprints) of the scene and then estimates the location of the tagged objects by matching the online measurements with the closest deductive location fingerprints [39]. One of the most common approaches is RSS location based fingerprint. There are two stages in the location fingerprint: the offline stage and the online stage (run-time stage). A site survey is performed in certain environments during the offline stage. The locations of the coordinate values, or labels, and the signal strength are determined by collecting nearby measuring units. In the online stage, the current detected signal strength and the gathered information are used to discover the new estimated location. However, errors can happen in received signals whose strength can be influenced by reflection, diffraction and scatter that occurs in indoor environments [39].

Fingerprinting-based positioning methods typically consist of five pattern recognition techniques including probabilistic, kNN, neural networks, SVM, and smallest SMP [39].

2.5.3 Proximity

In this method, the location depends on the symbolic relative location that is derived from an intense grid of antennas. When a mobile target enters the single antenna's radio signal range, the antenna will consider the target as a collocated object on its entire coverage. If more than one antenna detects the same target, it will be collected by the antenna that receives the strongest signal. The cell of origin (COO) defines the position of the mobile target and if the positon is within limited coverage. The localisation method is simple, and does not require heavy implementation. However, the accuracy relies on the density of the antennas and the strength of the signal range. This also means that the approximate position of the tagged object is used at a given time.

Table 5 compares three main types of tracking technique methods that used in RFID indoor localisation. Triangulations method; including Lateration and angulation, scene analysis, and proximity. Table 6, describes scene analysis (fingerprint) algorithms along with common work in each from the literature.

Table 5. A comparison between RFID localisation methods

RFID localisation technique		**Method**	**Dimension**	**Advantages (A)** / **Disadvantages (D)**	**Reference**
Triangulations	*Lateration Techniques*	TOA	2D	A: High precision localisation D:direct TOA suffers from synchronisation and time-stamp multipath effect.	Shen et al. [83]
		TDOA	2D	A: Accurate for Real-time locating (RTLS) D: NLOS Multipath	Kim et al. [84]
		POA/PDOA	2D	D: Multipath propagation Rely on LOS	Povalac [85]

		RSS	3D	A: -Cost effective method of location estimation -Better estimate of the distance. D: uncertainty location related issues	Chawla et al. [86]
	Angulation	AOA	2D, 3D	A: no synchronization required D: multipath reflections	Azzouzi et al [87]
Scene Analysis (fingerprint)		**(Refer to Table 4)	2D,3D		
Proximity		Reference points (well-known position)	2D	A: offer proximate position information D: cannot give absolute (relative) position	Song [88]

Table 6. Algorithms in RFID Scene Analysis (Fingerprint)

Scene Analysis Algorithms	**Description**	**Author**
Probabilistic Approach	Based on Bayesian network [86] to estimate target (tags) location.	Seo et al. [89]
k-nearest-neighbour (kNN)	Radio mapping based in online RSS.	Ni et al. [63]
Neural Networks method	It uses offline RSS and a-like location coordinates as an input for the target training purpose.	Moreno-Cano et al. [90]
SVM	It uses statistical analysis and machine learning to perform the classification and regression.	Yamano [91]

2.6 Challenges of RFID Localisation in Smart Homes

The main challenges of RFID location tracking systems and technologies are the high variation of principles and functionalities in localising objects and moving subjects in indoor environments. Researchers have worked on finding optimal indoor localisation solutions that worked across numerous indoor positioning platforms. Nonetheless, there is no fully optimal solution using RFID platform technology.

2.6.1 Accuracy-related Challenges in Tracking Entities in RFID Systems

2.6.1.1 Behavioural Variation of RFID tags

One of the most common problems facing passive RFID tags used in tracking systems is the fact that passive RFID tags fluctuate in their RSSI readings, even if the tags and readers are static (in a fixed position) and no objects or subjects are crossing one another. Furthermore, tags that are working in the same conditions may be different in RSSI. These behavioural variations could be caused by manufacturing defects or even differences within chips, integrated circuits and noise [47]. More approaches and methods need to be undertaken in order to calculate the RSSI changes and RFID tags' abnormal behaviour.

2.6.1.2 Behavioural Variations of RFID Readers

Another common issue in RFID localisation systems is behavioural variations. This happens when the readers are not able to fully query the tags within their reading range [92]. This could be addressed by finding a mechanism that can increase the power level and also by finding ways to optimise the distance between the tags and readers within acceptable reading values and without significant changes in RSSI readings.

2.6.2 Interference

Interference is a common issue in RFID localisation. It is caused by environmental interference factors like radio noise and collision caused by impermeable metal and liquids, meaning the signal cannot pass through it. Internal factors related to RFID such as tags and readers can also create interference. This causes RF propagation and eventually leads to errors in localisation [64]. The interference problem can affect both active and passive tags in localisation. However, in active mode tracking, the localisation errors are less than in passive tracking because the active RFID readers emit less energy to detect the tags. In passive tracking, RFID readers require more energy to localise the passive RFID tags that do not have any source of energy and rely on the RFID reader's emissions. UHF RFID interference can be divided into three types including tag interference, multiple readers to tag interference and reader to reader interference [93]. Research has proposed to reduce localisation errors caused by interference [94] [95] but unfortunately, further investigation is required to produce better and more scalable results.

2.6.3 Tag related problems

Tag orientation is very important for detecting a tag's location via reader communication. Tags can be attached vertically, horizontally or at an angle on the sides of objects to obtain better detection. Parallel orientation usually reduces the chance of detection compared to the previous setup due to one side of directivity in a parallel orientation.

The sensitivity of tags is another issue in RFID localisation applications. It defines the minimum power required to activate or read the tags and those with lower sensitivity cause more location errors while tags with higher manufactural sensitivity provide better location detection [94].

Tag spatiality affects localisation errors. For example, frequent replacement of tags at random locations will lead to lower accuracy. Tags placement at specific and consistent locations will provide better results during the interactions between readers and tags.

2.7 Activity in Daily Living in Smart Homes for Healthcare

The activity in daily living (ADL) refers to the things that individuals do in their daily life such as work, homemaking and leisure and particularly their daily self-care activities such as feeding, bathing, dressing and grooming [96]. These activities define the individuals' ability to live independently in residential homes. ADLs are categorised into two main groups, basic activity in daily living (BADL) and instrumental activity in daily living (IADL). BADLs are the necessary basic domestic or routine activities required for an individuals' wellbeing including mobility, eating, drinking, sleeping, dressing, bathing and going to the bathroom. On the other hand, IADLs are other tasks that are not crucial for life. However, IADLs provide comfort for the elderly people and impaired individuals and include housework, food preparation, medication, exercising, shopping, ironing, sweeping, telephoning, etc.

The recognition of human activities in indoor environments is a difficult task to achieve [97]. ADL focuses on addressing these challenges and finding solutions to understanding human activity in Smart Homes. Ubiquitous environments like Smart Homes have facilitated the detection of daily activities by deploying various environmental sensors such as RFID, wearable sensors and vital signs sensors to collect data such as location, movement patterns and patient health status. The data is then translated to descriptions of activities using models and algorithms within context-aware systems and computerised applications.

2.7.1 Sensors for Activity in Daily Living

There are three main groups of sensors for human activity recognition including wearable based, physical environment based and other sensors as shown in (Figure 2.5)

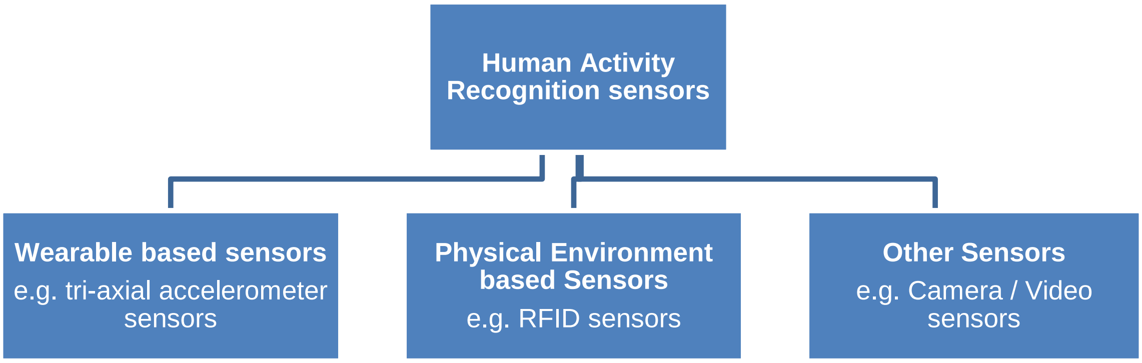

Figure 2.5. Human Activity Recognition Sensors

2.7.1.1 Physical Environment Based Sensors

Types of sensors such as RFID, Proximity, Pressure, Zigbee, and WLAN can be used to detect the interaction between the person and the environment around them [98]. Environmental variable based sensors use the raw data from sensed objects to assume the nature of activity undertaken by the individuals [98]. The distributed sensors detect the a person’s activity and their interaction with objects. The data is collected by the ubiquitous sensors and is then sent to a local server for further processing.

2.7.1.2 Wearable Based Sensors

Wearable sensors such as inertial sensors, accelerometers, electromechanical switches, goniometers and pedometers gyroscopes are body-attached sensors and are one of the most common sensors for human activity recognition. They are used to recognise the motions of a human body and to support the human recognition movements as well as fall detection using wireless monitoring systems [99]. The devices are designed to continuously measure physiological data such as vital signs of the human body, as well as biomechanical data. Analysing such data helps to identify human activities in daily living and translate them into a meaningful form using pattern recognition [100].

2.7.1.3 Other Activity Recognition Sensors

Camera based sensors, which are widely used for human activity recognition within a finite sensing coverage are those sensors which rely on the cameras recording and video sequences to recognise the human activity using computer vision algorithms [98]. Video sensors such RGB video [101], RGB-D video [102] and depth images sensors [103] are common types of visual sensors and are broadly accepted in human activity recognition with good recognition rates. However, they are costly, have high energy consumption and also require frequent maintenance and are subjected to privacy related concerns

2.7.2 Problems Related to ADLs in Smart Homes

Activity misclassification - This problem happens when the method cannot distinguish between BADLs and IADLs [104].

Specific activities - Some of the BADL activities such as making a sandwich and making toast are usually classified as the same, however, they are different activities and need to be identified differently in the discriminated model [105].

Ambiguous activities – These occur when activities appear that are not predefined in the training model. These may also happen when several sensors and objects are activated at the same time so that the system reports the same activity from different sensors. For example, most of the systems classify lying in a bed as sleeping but cannot actually determine whether a person is sleeping, reading a book or watching TV [106, 107].

The current issues related to ADLs in Smart Homes are summarised in Table 7.

Table 7. Current issues in ADLs in Smart Homes

Activity	**Activity Level**	**Nature of problems**
Ironing	IADL	Misclassified between two different activities (e.g. confusion between ironing and dressing [104])
Dressing	BADL	Misclassified (e.g. confusion between ironing and dressing [104])
Washing Dishes	IADL	Misclassified (e.g. confusion between washing dishes and clothes [104])
Brushing teeth	BADL	Misclassified (e.g. confusion between brushing teeth and washing dishes [104])
Sleeping	BADL	Ambiguous with other activity (e.g. ambiguity between recognising sleeping from reading a book or lying in bed or watching TV [106])
Making sandwich/ toast	BADL	Specific activity (e.g. most systems cannot distinguish between particular food activities such as making a sandwich from making toast [105])

2.7.3 Research Challenges in ADL

ADL detection is still a difficult task to achieve in Smart Homes with regards to healthcare requirements. Many approaches have been introduced towards solving ADL recognition problems. However, there are still limitations. The following table (8) summarises current challenges of ADLs as perceived from the literature.

Table 8. Current research challenges in ADLs

Challenges	**Description**
Accuracy and robustness in activity recognition [108]	Some human activities can be carried out by different humans at different times. The actions that are taking place rather than evaluate how correctly the activity was carried out as well as other qualitative information.
High-level and long-term activity monitoring [108]	Monitoring high-level activity in large-scale data [49] and a real-world scenario is still difficult to achieve, and needs proper formalisation of activities. Long term activities usually include several sub-activities that may be performed in different order.
Multi-user and multi-sensor activity monitoring [108]	In lab experiments, the data are usually collected by a single user activity. However, in a in real life scenario, activities can be performed by multiple users concurrently and there may be interaction between them. Multiple sensors are still a research challenge.
Real world data collection [108]	Most of experiments and ADL activities are carried out in laboratories where designs and solutions are based on lab settings. The activities that are performed in the lab are also based on the lab environment.
Behaviour trend profiling and analysis from monitoring sensor [109]	Long-term monitoring poses some challenges such as data labelling and issues of profiling and analysis with data integration.
Affective states detection [109]	How successfully affective states are identified and performed (e.g. happiness, sadness, anger, etc.). Activities that monitor human physiological parameters could contribute significantly to behaviour trend analysis.
Distinguishing between fall and ADL events[108]	Distinguishing between falls and ADL events still poses challenges, though each event has distinct characteristic signatures in the sensor data.

Within the scope of this thesis, the development of ADL tasks has not been carried out.

3 FRAMEWORK AND EXPERIMENTS

Explored throughout this chapter is the methodological framework of our proposed indoor RFID location system using passive RFID sensors to localise our target. Ultimately, the goal was to optimise the accuracy using minimal and affordable tracking resources. The system utilised implementation of the RFID localisation test bed setup, evaluation, sensors calibrations, localisation algorithms and experiments. Low cost passive RFID-based sensors were utilised with the overall aim of achieving a desirable accuracy of localising subjects and objects.

3.1 Environment

In this section, the design of the RFID system is described, including the core components and the setup environment. The experiments were deployed in the Smart Home infrastructure at the Telehealth Research & Innovation Laboratory (THRIL) at the School of Computing, Mathematics and Engineering (SCEM), Western Sydney University. The experimental test area was 2.75m × 3.0m. The testing environment was effected by other external influences including wi-fi network, metal stands, furniture, lab equipment and on occasion magnetic field from other labs so as to replicate a real-life scenario. The system was deployed inside THRIL lab room and covered the majority of the room’s floor area. RFID sensors were located around the room with an average temperature of 22-24°C in accordance with the recommended operating temperature from the manufacturer (Impinj technologies).

3.2 System Design and Setup

This section describes the system design, deployment and implementation of the hardware and software components. The integration of both components enabled evaluation of the localisation approach using passive RFID (see Figure 3.1).

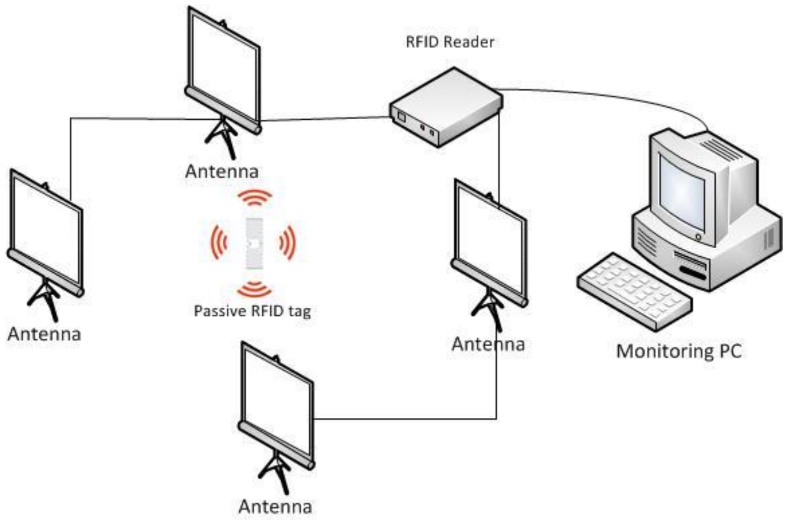

Figure 3.1 An example of our hardware setup

3.2.1 Hardware Components

This section provides a brief description of the equipment and hardware that were used in our experiments.

3.2.1.1 Reader

Impinj is a provider of a range of RFID readers. For our system requirement and space localisation needs, "Speedway Revolution R420" was selected (see Figure 3.2).

Figure 3.2 Impinj Speedway Revolution UHF R420 RFID Reader

The R420 RFID reader provided the following features which were suitable for our requirements:

- The device had four ports which were expandable up to 32 antennas using Antenna Hub to reduce the system expansion cost and achieve flexibility in various applications.
- It provided high RF read sensitivity up to (-84dBm) which was useful to improve accuracy and ensure a longer reading range.
- It was relatively easy to install. Moreover, its interface could connect to a personal computer using a Power over Ethernet (PoE) port.
- The device had a decent Application Program Interface (API) that used Java programming language.

3.2.1.2 Antenna

Impinj provided the RFID antennas together with the Speedway Revolution kit. The antenna (series S9028PC, Figure 3.3) worked at the maximum frequency received by the reader within an operating frequency range of UHF 860- 960 MHz, region dependent.

Figure 3.3 UHF RFID antenna type S9028PC

3.2.1.3 Tags

Based on our system design, only passive tags were utilised. A collection of passive RFID tags of different sizes and models were obtained. Each type had strengths and weaknesses. We selected the best tags from the collection by applying a systematic tag selection procedure. The selection identified candidate tags for the planned localisation experiment.

3.2.1.4 Hardware Setup

The physical platform setup was divided into two components; the first was to examine target tags using a trilateration algorithm and three antennas (Figure 3.4 a). The second setup localised the target using multilatertion and four antennas (Figure 3.4 b). Physical setup was implemented in (2.75m * 3.0 m) test area.

a　　　　　　　　　　　　　　　　b

Figure 3.4. Visual Localisation Testbed, where a) 3 antenna setup and b) 4 antenna setup

Due to limited space, human body impacts, and environmental effects such as interference from metals bars, tables, cables, and wireless transmitting devices attempts were made to reduce the environmental noise by isolating the obstacles at the rear using wall attached furniture pieces (see Figure 3.4 b).

Antenna angle and coordinates were measured using the laser measurement technique to achieve the most accurate readings from all antennas (see Figure 3.5).

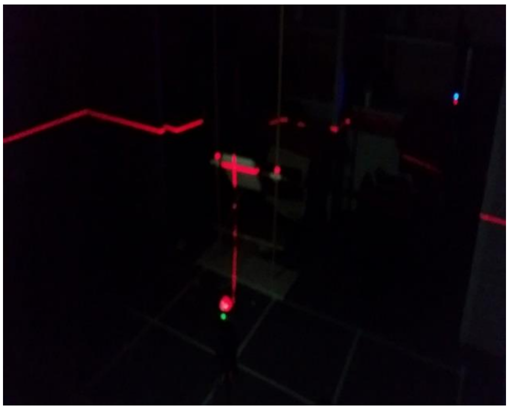

Figure 3.5. Adjusting an equilateral triangle with a laser guide

To achieve the best overall performance of the antennas, antenna tendency was set up at 45 degrees facing the floor, as recommended by Impinj Technologies. The preparatory test showed that RSSI values were the highest at 45 degrees from each antenna. Therefore, experiments were undertakenbased on the suggested design and RFID sensor setup. Table 9 shows the technical specification of our localisation platform setup.

Table 9. Technical specifications of our localisation system

Components	Information
RFID development kit	**Reader:** Impinj R420 UHF RFID x 1
	Antenna: Near- and far-field reader antennas x 3
	Tags: EPC global UHF Gen 2 (MONZA types tags)
Monitoring machine	**CPU**: AMD Phenom II X4 945 Processor 3.00 GHz /**RAM**: 3 GB / **Hard-Disk**:232 GB / **Operating System**: Windows 7
Application Interface	Java IDE
Test Bed	Localisation grids floor 2.75m* 3.0 m.

3.2.2 Software Components

The software in the tracking experiment included two components. The first component used *MultiReader* inbuilt software to connect the RFID readers and reads the tags (see Figure 3.6). Using this software at the first stage helped in interpreting the behaviour of the tags during the selection process. The second component used Impinj's Application Programming Interface (API) in Java programming language to retrieve RSSI values for positioning and calculating coordinates.

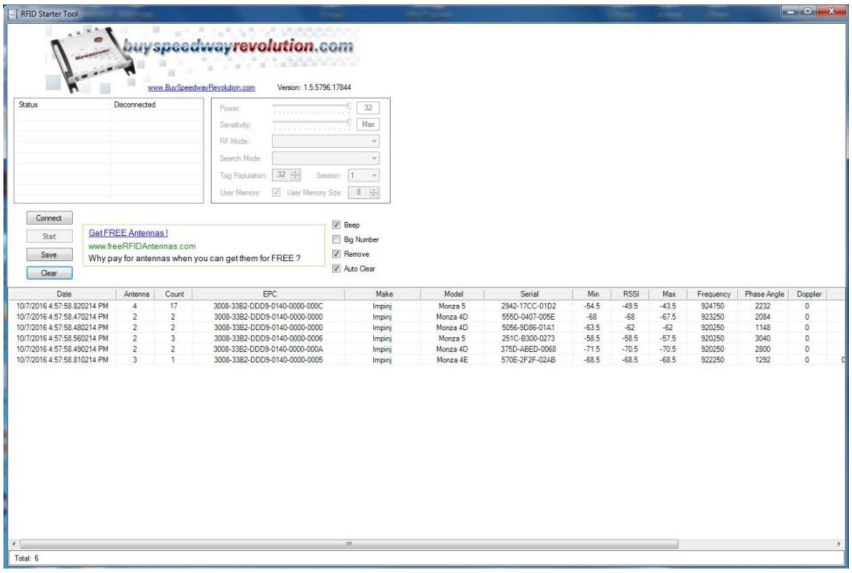

Figure 3.6 MultiReader v6.6.13 software application from Impinj Technologies

The second component consisted of four main parts, including *ReadTag*, *TagReportListnerSetup*, *Graphical* and *MainProgram* files.

Tag reading established the connection with the reader by telling it to start performing measurements and retrieve RSSI values. A text file was generated and the information saved for further analysis.

Tag reporting relayed the required information to the console command or via a text file. Program setup took measurements such as RSSI, phase angles, Doppler frequencies, time of the test, and the EPC of each sensing tag. The program converted RSSI values into distant values from a distance formula and coordinates by using the *trilateration* and *multilateration* algorithms.

The graphical class file was used to visualise the outcomes. Java graphics library was then utilised to setup and draw the coordinate systems. It then visualised the output in real-time using the coordinate data from the Tag Report file. This process allowed location tracking of the target tag in real time.

3.2.3 Data Analysis

This experimental process used MATLAB to analyse the results and conduct data manipulation. The program also evaluated our localisation algorithms in the first initial localisation stages by analysing the sensor's raw data and applying several tracking algorithms to justify these inputs, and to generate valid and meaningful outputs. (See Figure 3.7). The analysis processes involved examining the RSSI values received from each tag. The RFID tags were sensed by RFID reader, then the Java API stored RSSI raw data values for further analysis in MATLAB.

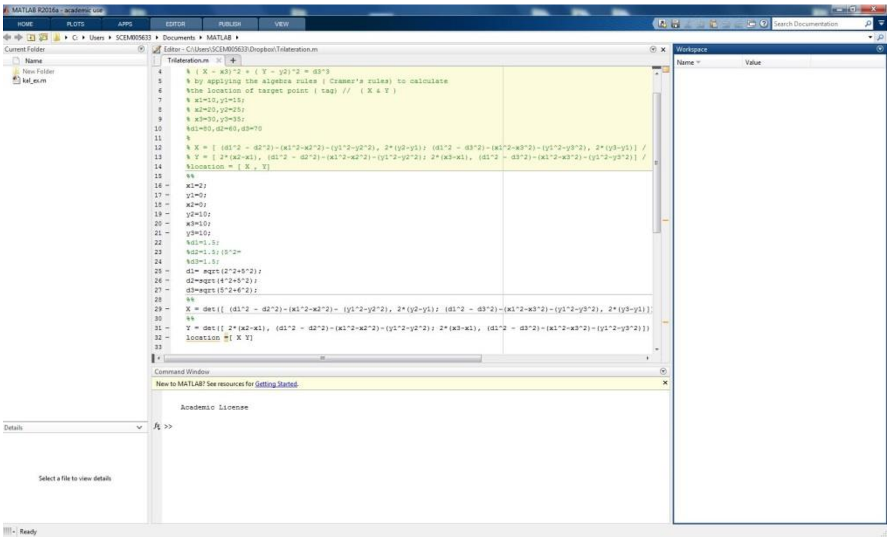

Figure 3.7 MATLAB R2015b for RSSI and data analysis

3.2.4 Received Strength Signal Measurements (RSSI)

Successfully performing localisation is not possible without knowing the RSSI values from the RFID reader. Therefore, in order to send the values to our Java program, Octane Simple Network Management Protocol (SNMP) from Impinj was used with Octane standard MIB-II SNMP [110]. We used the software development kit SDK provided by Impinj to establish connections with the RFID reader. Our program was also able to retrieve the RSSI (*peakRSSI*). Further details are discussed in the following chapter.

3.3 Passive RFID Localisation Framework

A system was introduced that used a minimal number of antennas and one passive tag for object localisation. Various devices and technologies supporting localisation and tracking of objects in Smart Homes were also used.

To justify our hypothesis of tracking using minimum resources, we divided our proposed localisation framework to three main localisation processes. Firstly, the tag selection stage was carried out to select the most desirable tags that performed well under a range of situations. Secondly, sensor and tag calibrations were implemented to ensure uniform performance of a tag at a number of calibration processes, such as antenna height, tag orientation and antennas calibrations. Finally, suitable algorithms were implemented to estimate our target tag positions at a stationary location and were extended to cater for moving subjects.

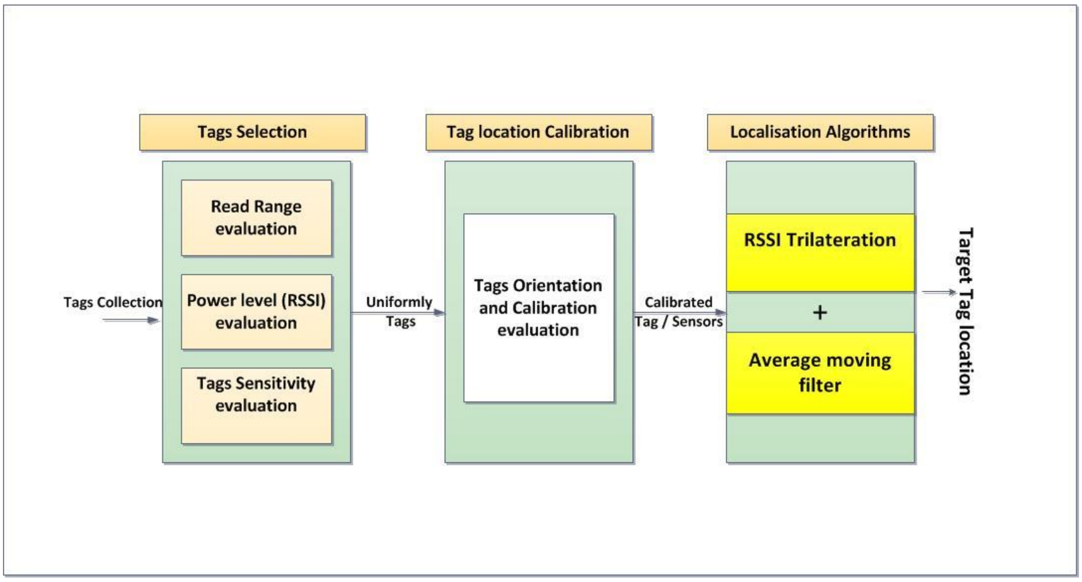

Figure 3.8. Localisation processes of passive RFID-based objects and subjects

3.3.1 Tag Selection Procedure

Twenty tags were selected from Impinj and were examined in the selection process to identify the best tags and ensure they would perform well in other tests.

A methodology was designed to select the candidate tags for the localisation process with a specific selection criteria. The first stage of the localisation process was to enter all tags into the selection procedure to determine the most suitable and readable for our localisation purpose. This involved several steps to define which tags were chosen for the next stage in our localisation framework. At the first procedural test, the read range evaluation examined the tags' reading ranges from various distances from the RFID antenna. This was achieved by determining which tags were still readable at the furthest distance from the antennas. The following test examined the tag reading based on different power levels of the reader, where the tag was set at a fixed location from the antenna. A tag sensitivity test determined the most suitable tags in the collection from the readings of various sensitivity levels.

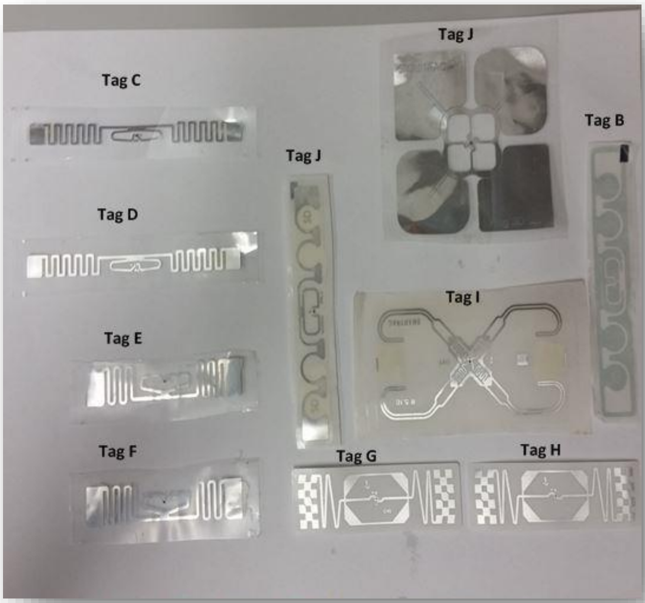

Figure 3.9. MONZA tag types used in tag selection experiments

3.3.1.1 Reading Range Selection

Passive RFID tags have a different level of performance. In general, small tags have smaller antenna circuits which results in poor performance. This test aimed to observe the tags' reading performance at specific distances with a maximum power level of 32dBm, and at maximum sensitivity. This procedure ensured and determined the best tags which were readable at greater distances. Tags were placed in a measurement line starting at 0.5m then the distance was increased in 0.5m increments until it reached 4.0m. All tags faced the designated antenna for this test, and RSSI readings were reported for further analysis.

In this test, the relationship between the distance in meters and tag readings in RSSI were analysed to find the distance formula which could be applied to tag location measurements later on.

3.3.1.2 Power level-RSSI Selection

This test was designed to examine the performance of each tag under different power levels by varying the power levels from the reader from 20dBm to 32dBm and then the RSSI readings of each tag were recorded.

3.3.1.3 Tags Sensitivity Selection

Similar to the power level RSSI selection, this test evaluated the behaviour of tags amongst different level of sensitivities. The range of sensitivities was -90, -70, -60, -50, with a maximum power level and varying tag distances.

The aforementioned tag selection procedures were completed, the tag that was still readable after various procedural selections, was selected the designated prime tag for our localisation purposes.

3.3.2 Tags Calibration Procedure

After the selection process, the candidate tags were further tested using various stationary locations and orientations to evaluate tag readings at different directions from the antennas. This procedure also evaluated tag performance amidst a set of nearby tags to determine the impact of neighbouring tags on the target RSSI values. In other words, this test observed the characteristics of reference tags in relation to the target tag. This procedure was essential to select the most suitable tag as the orientation was an important factor in deciding the performance of tag.

In this experiment, all the antennas were located in fixed positions on a gridded floor. The antennas were facing the target tags at the same height. Various power levels were set to find the optimal power level of each antenna. Other factors, such as tag orientation and antenna angulation, were examined to obtain the proper settings of our localisation platform.

3.3.3 Localisation Procedure

After meeting the requirements of the previous tests, we intended to use the selected tag with target subjects or objects to estimate the location and evaluate our platform performance. Further, our goal was to optimise the accuracy using minimal tracking resources and achieving the highest accuracy required to understand the appropriate localisation theories and formulas and to use the correct algorithms which will be addressed in the following sections.

3.4 Received Signal Strength Indication (RSSI)

3.4.1 Radio Wave Propagation Passive RFID Model

Typically, a passive RFID tag does not have internal batteries, therefore, it relies on an RFID antenna to receive enough radio power to become activated and reflect power back to the antenna. This mechanism is called backscatter (Figure 3.10).

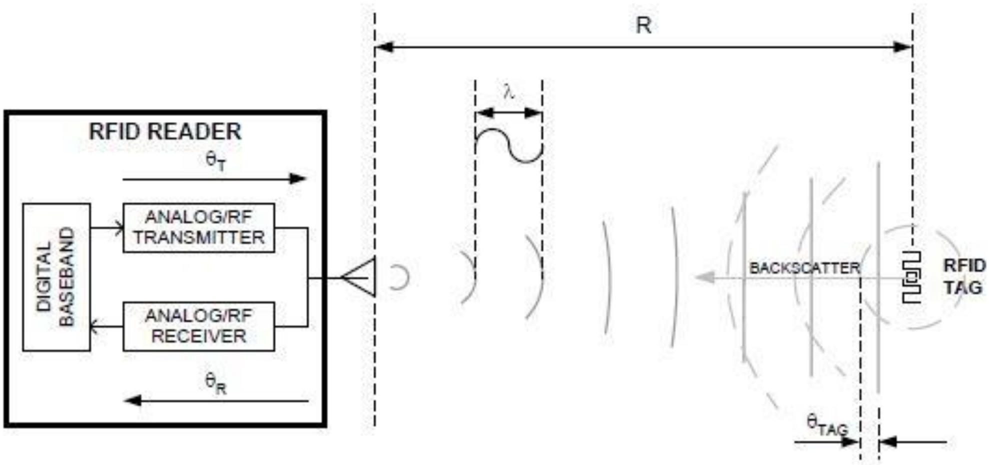

Figure 3.10. Radio wave propagation model between RFID reader and tag [111].

The following equation represents Friis equation [112] to estimate the tag backscatter Power Received (PR) by a RFID Reader.

$$P_R = \frac{G_T^2 \lambda^2 \sigma}{(4\pi)^2 R^4} P_T \tag{1}$$

where,

P_T = Reader transmits power at the transmit antenna input (Watts)

G_T = Reader antenna gain

λ= Carrier wavelength (meters)

σ = Tag Radar Cross Section (meters^2)

R = Distance between reader and tag (meters) [111]

3.4.2 RSSI Theoretical Model

Wireless Sensor Network and Active RFID systems measure the received signal strength indicator (RSSI) using RF-sender to RF-receiver system as indicated in equation [113]. Nevertheless, this equation does not suit passive UHF RFID systems because passive tags are unable to measure the strength of incoming power [113].

Once a passive tag receives the power transmitted by the reader, represented by backscattering power at the tag side (equation 2), a portion of the power will be reflected from the passive tag back to the reader antennas (equation 3).

$$\boldsymbol{P_{tag}^{RX} = \frac{P_t G_t A_e}{4\pi R^2}} \tag{2}$$

Where A_e is the effective aperture of the tag

$$\boldsymbol{A_e = \frac{G_{tag}\,\lambda^2}{4\pi}}$$

$$\boldsymbol{P_{tag}^{TX} = P_{tag}^{RX} / L} \tag{3}$$

where, $\boldsymbol{L}$ is transmission loss ratio

In theory, Path Loss Module and Friis equation [112, 114] will be applied to measure RSSI at the interrogator's antenna.

3.4.3 RSSI to Distance

Based on our observations from previous preliminary experiments, we found that there was an existing relationship between the average value of the RSSI and the tag distance from the antenna in static locations. It was necessary to obtain the correct formula to measure the distance from the RSSI values for further application processes such as location detection in indoor location systems. In experiment, Friis equation converted to an approximate linear logarithmic distance equation [115, 116] Taking in consideration confined environment, we have considered using the method [117] to determine the distance between RFID tag and RFD antenna.

3.4.4 Localisation Algorithms

Our localisation approach targeted passive tags (i.e. movable and non-expensive) that could be easily attached to impaired individual's assistive devices such as a wheelchair, or walking stick. To achieve this goal, multiple algorithms have been studied including trilateration algorithms [23, 24] for distance estimation and filtering algorithms. We now present the localisation algorithms.

To determine Received Signal Strength Indication (RSSI) values, loss path propagation model [114] derived from Friis Transmission Equation [112] was studied to estimate the tags backscatter signal power received P_R. In experiments, Friis equation converted to an approximate linear logarithmic distance equation [115].

After measuring the distance of the passive RFID targeted tag using the methods mentioned above, the well-known trilateration algorithm [48, 118] was applied to estimate three distance points from each antenna around the targeted tag. The system performed the trilateration to estimate the location of the targeted tag in real time. The position of the target tag was calculated usiong the intersection of the three circles.

Due to the noise and the major changes in RSSI values, filtering was essential to ensure the quality and smoothness of the reading signals. Although there were many different types of available filter algorithms, at that stage, we only applied the moving average filter to reduce the noises from the readers. The filter use the average of every (N) sequential readings from each RSSI sample. It then reduced the mean of the distance variance of each estimate and the actual position [119]

3.4.4.1 Localisation using RSSI Trilateration Module

Trilateration is one of the simplest localisation approaches used to estimated locations in indoor positioning systems. The principle of this approach requires knowing the positions of three reference points (three antennas). The RSSI values received by each antenna from the target tag were converted to RSSI to three distances; d_1, d_2 and d_3 respectively from each antenna to perform position estimation. Based on our initial antenna design, the target tag was determined by estimating its coordinates using the well-known geometric trilateration algorithm [120] to estimate the tracked position in 2D. In trilateration, the estimated location was determined by calculating locations of points by measurement of distances. This required using the geometric characteristic of a triangle, sphere and circle to determine the target location. In RFID systems, the target location is converted to RSSI values of the tracked tag from each antenna to generate three distance values (d_1, d_2 and d_3. The mobile user can then be located by determining the intersection of the three circles and knowing the real coordinates of each antenna (see Figure 3.11).

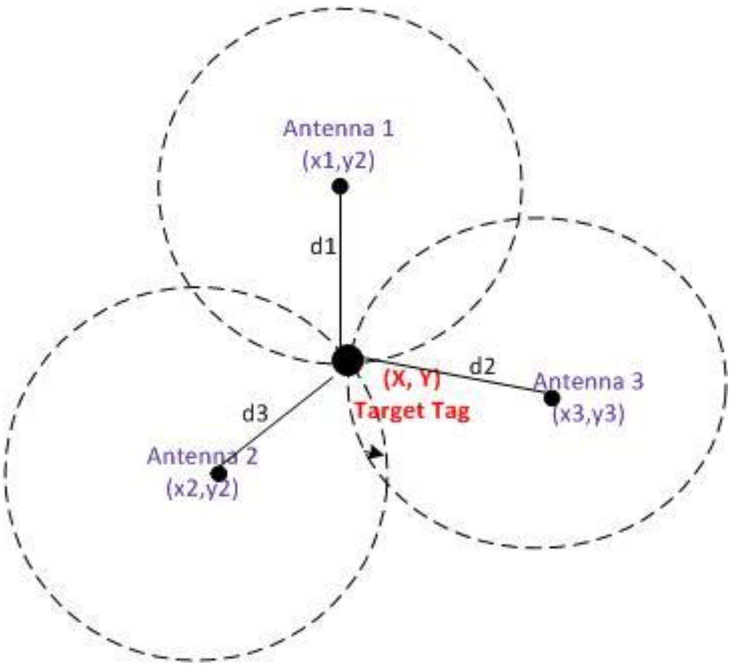

Figure 3.11 Trilateration locations estimation

Based on the coordinates of the three antennas $(x_1, y_1), (x_2, y_2)$ and (x_3, y_3) and the corresponding distances d_1, d_2 and d_3 from each antenna to the target tag. The trilateration formula was then applied to determine the coordinate of the unknown target tag location (X,Y).

$$
\begin{aligned}
(x1 - X)^2 + (y1 - Y)^2 &= d1^2 \\
(x2 - X)^2 + (y2 - Y)^2 &= d2^2 \\
(x3 - X)^2 + (y3 - Y)^2 &= d3^2
\end{aligned} \tag{4}
$$

To solve the system of the three equations with three variables using Cramer's rule, we determine *X* and *Y* coordinates as follows:

$$
\boldsymbol{X} = \frac{\begin{vmatrix} (d_1^2 - d_2^2) - (x_1^2 - x_2^2) - (y_1^2 - y_2^2) & 2(y_2 - y_1) \\ (d_1^2 - d_3^2) - (x_1^2 - x_3^2) - (y_1^2 - y_3^2) & 2(y_3 - y_1) \end{vmatrix}}{\begin{vmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \end{vmatrix}} \tag{5}
$$

$$
\boldsymbol{Y} = \frac{\begin{vmatrix} 2(x_2 - x_1) & (d_1^2 - d_2^2) - (x_1^2 - x_2^2) - (y_1^2 - y_2^2) \\ 2(x_3 - x_1) & (d_1^2 - d_3^2) - (x_1^2 - x_3^2) - (y_1^2 - y_3^2) \end{vmatrix}}{\begin{vmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \end{vmatrix}} \tag{6}
$$

3.4.4.2 Localisation Using Mulilateration Module

Similar to the trilateration principle, multilateration [121] determines the location of passive RFID tags by calculating the distance (d_1, d_2 , d_3 and d_4) of the target tag from each antenna at known locations (x_1, y_1), (x_2, y_2), (x_3, y_3) and (x_4, y_4). (See Figure 3.12).

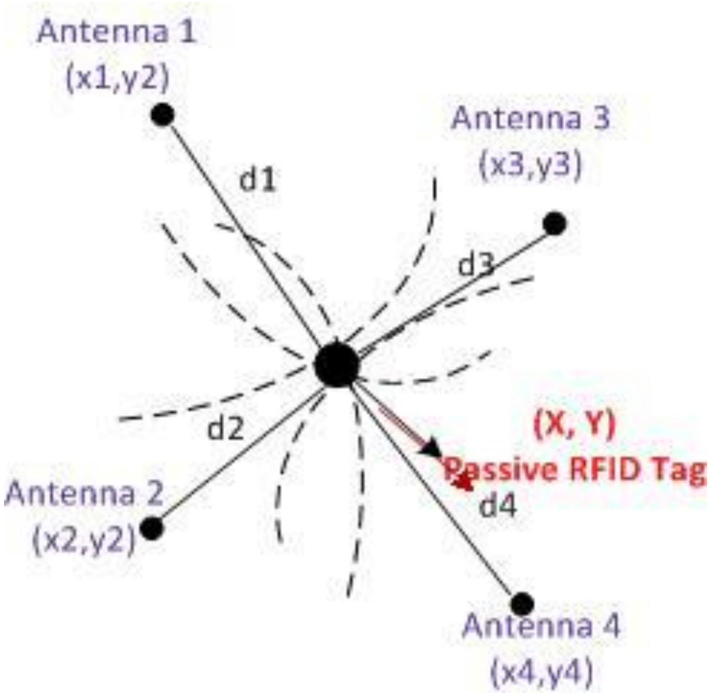

Figure 3.12 passive RFID tag location estimation using the multilateration algorithm

The intersection of multiple hyperbolic curves identifies the estimated locations of the target passive RFID tag. This method is also called TDOA (Time Difference of Arrival). The pseudocode of the localisation procedure is shown in Algorithm 1.

Algorithm 1 localisation procedure

Input: Antennas
TagID(target Tag)
RSSI(series of values for each antenna)

Output:
Location(X, Y)
var ant = count.AntennaNumbers();
for (each recorded series of RSSI from each antenna)
do
$SMA\ (\frac{1}{n}\sum_{i=0}^{n} RSSI_i\ )$
end do
new RSSI = SMA(RSSI)
switch (ant)
case A:
if (ant == 3)
do (Trilateration)
end if

```
  case B:
    if (ant > 3)
      do ( multilateration)
    end if
  end switch

  return location
```

3.4.4.3 Filtering Algorithms

Signal filtering is an essential step in indoor localisation systems because several environmental factors can significantly affect the signal's readings such as multipath, human body chaos, nearby magnetic fields, other wireless communication interference (e.g. Wi-Fi) and other environmental interference related problems. It is important to acquire the right signal filtering with a view to disregarding the irregular signal readings.

3.4.4.3.1 Simple Moving Average filter (SMA)

In order to reduce the noise in RSSI readings (odd values), a smoothing filter is required to perform this task. A simple moving average filter is one of the simplest signal smoothing techniques which reduces the offbeat RSSI readings. An array of RSSI raw (noisy) data (x1, x2, …, xn) can be converted to a new array of smoothed RSSI data as appears in the following equation (9) which was implemented in our localisation program.

Array of RSSI raw (noisy) data $\{x_1, x_2, \ldots, x_n)$ can be converted to a new array of smoothed RSSI value as shown in (9). (7)

$$\boldsymbol{SMA = \frac{x_1 + x_2 + \cdots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i}$$

where x_i refers to *i*th RSSI (*n*) number. The above SMA is implemented in our localisation program. The pseudocode of the SMA is shown in Algorithm 2.

Algorithm 2 Simple Moving average Filter

Input: RSSI series (for each antenna)

Output: RSSI` after removing odd readings

```
  var A = (RSSI ≠ 0)
  var P = (moving filter length)
  var x = 1:length(A)
```

```
for n = 1:length(A)
  if n > P
     average(n)=mean(A(n-P+1:n))
  else
     average(n)=mean(A(1:n))
  end if
end for
```

4 RESULTS AND ANALYSIS

This chapter presents the experimental results and the evaluation of the proposed localisation framework. Several experiments were conducted to evaluate the new localisation platform using passive RFID technology. The results highlighted the distinct aspects of our localisation framework using passive RFID tags in procedural steps. This chapter also provides an discussion on the results and findings of each experiment.

4.1 Experimental Results and Evaluation

In this section we present the experimental setup, steps and testing procedures of our entire passive localisation framework. We performed extensive experiments to validate our localisation approach to determine the potentials and the limitations of our tracking platform.

The experiments were grouped into three sets of experiments. The purpose of the first set was to choose the suitable tag amongst candidate tags for localisation purposes, by evaluating all tags using a specific procedural tag selection method. The second set of experiments was conducted to determine the characteristics of the elected tag from the previous experiments. By calibrating and configuring both tag and RFID tracking antenna, we aimed to achieve the best calibration procedure to contribute toward obtaining the desired accuracy. Finally, this thesis investigated and evaluated the performance of the target tag using geometry localisation algorithms and RSSI filtering. This tag was affixed either to a stationary object or to a walking stick handled by moving individuals.

4.1.1 Tag Selection Procedure

This procedure was significant in determining the right tags for the localisation process. The goal of the test was to select the most feasible tags amongst others. Twenty tags were incorporated into the selection process at the preliminary stage (see Figure A.36, Appendix A). We were able to narrow down the selection to choose only ten tags as candidate tags and to examine them in the multilateration (see Figure 4.1 and Table 10). The first procedure tested all candidate tags' RSSI reading ranges. In the second selection, all tags were tested under various power levels in (dBm) to evaluate which tags were still responding well at various power levels. Finally, a tag sensitivity procedure was undertaken to evaluate the tags responses at different sensitivity levels.

a b

Figure 4.1 Tag selection procedures.

- a) candidate tags used in the tag selection and b) experimental tag distance reading selection setup

Table 10. Candidate Tag types

Tag type	Tag description
Tag A	Tag A - Monza 4D: EPC (0000-0000-0000-0000-0000-0002)
Tag B	Tag B - Monza 4D: EPC (3008-33B2-DDD9-0140-0000-1000)
Tag C	Tag C - Monza 4E: EPC (3008-33B2-DDD9-0140-0000-0005)
Tag D	Tag D- Monza 4E: EPC (3008-33B2-DDD9-0140-0000-0002)
Tag E	Tag E - Monza 5:EPC (3008-3382-DDD9-0140-0000-0004)
Tag F	Tag F - Monza 5: EPC (3008-3382-DDD9-0140-0000-0006)

Tag G	Tag G - Monza 4U: EPC (3008-3382-DDD9-0140-0000-0007)
Tag H	Tag H - Monza 4U: EPC(3008-3382-DDD9-0140-0000-0003)
Tag I	Tag I - Monza 4D : EPC (3008-3382-DDD9-0140-0000-000A)
Tag J	Tag J - Monza 5: EPC (3008-3382-DDD9-0140-0000-000C)

4.1.1.1 Tags Distance Reading Range Evaluation

In this test, we examined all tags performance at specific distances with the maximum power level of 32 dBm. After evaluating the results, we identify the most readable tags at the longest distances from the RFID antenna (RFID antenna on the floor with 90° orientation facing each tag). Furthermore, we were able to select the tags that can be read in a longer distance, as an important factor to achieve better performance.

Figure 4.1b illustrates tag distance reading (RSSI) results for the ten candidate tags. Note, that the lower RSSI values (e.g.-30), the better the readings we received. According to the observation, tag (A) showed the best RSSI readings among all candidate tags at different distances from the RFID antenna. This was due to the fact that tag A had a longer antenna circuit which was capable of sensing and absorbing more signal power coming from the antenna, and thus more efficiently reflected back RFID signal. In the preliminary tests, we disregarded the small tags with small antennas due to our previous initial observations.

Each pair of tags (such as C&D/ E&F/ G&H) came from the same tag type. Therefore, we examined the distance behaviour of the candidate tags by repeating the same test, while recording the overall performance. The results were presented in Figure 4.2 and Figure 4.3.

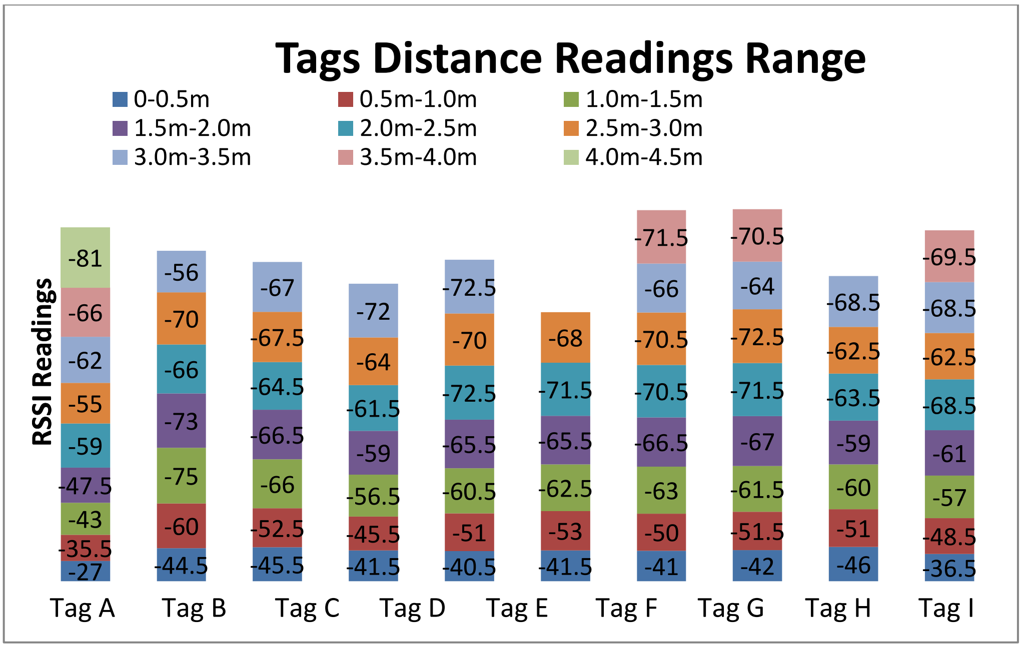

Figure 4.2. Tags Distance Readings Range.

Tag A = Monza 4D type 1, Tag B = Monza 4D type 2, Tag C = Monza 4E type 1, Tag D = Monza 4E type 2, Tag E = Monza 5 type 1, Tag F = Monza 5 type 2, Tag G = Monza 4U type 1, Tag H = Monza 4U type 2, Tag I = Monza 4D type 3, Tag J = Monza 5 type 3.

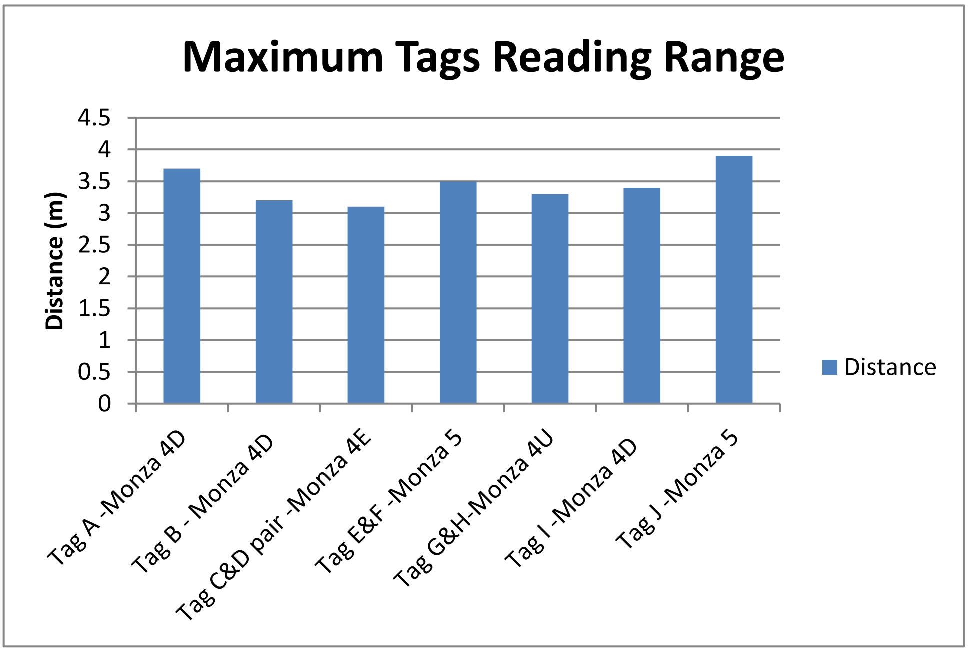

Figure 4.3 Maximum Tag Reading Ranges

Figure 4.4 clearly shows that tag A had the longest distance reading. . The tag was still readable and performed efficiently at a distance 3.7 meters (m).

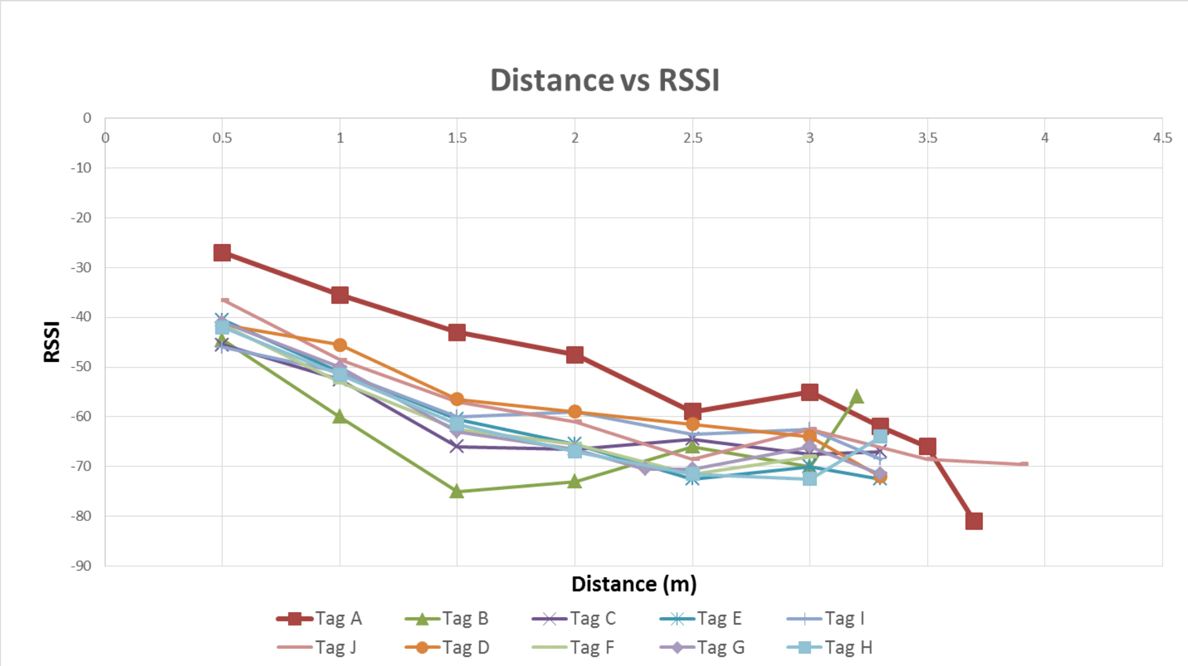

Figure 4.4 The relationship between RSSI and distance of all candidate tags

4.1.1.2 Power Level RSSI Selection

To achieve the best tag selection results from the selection procedure, another mechanism was required to test and measure the tags RSSI. We measured the backscatter from the reader-transmitted radio signals back to the reader. Power level metrics was determined to ensure that we selected the best tag across different reader power levels and various distances between the tag and the antenna. In this test we varied the reader power levels (32, 30, 25, 20), over a set of dBm at distances (0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 3.9) meters respectively. Figure 4.5 and figures in section Power Level RSSI Selection in Appendix A) show the candidate RSSI tag readings at different power level outputs.

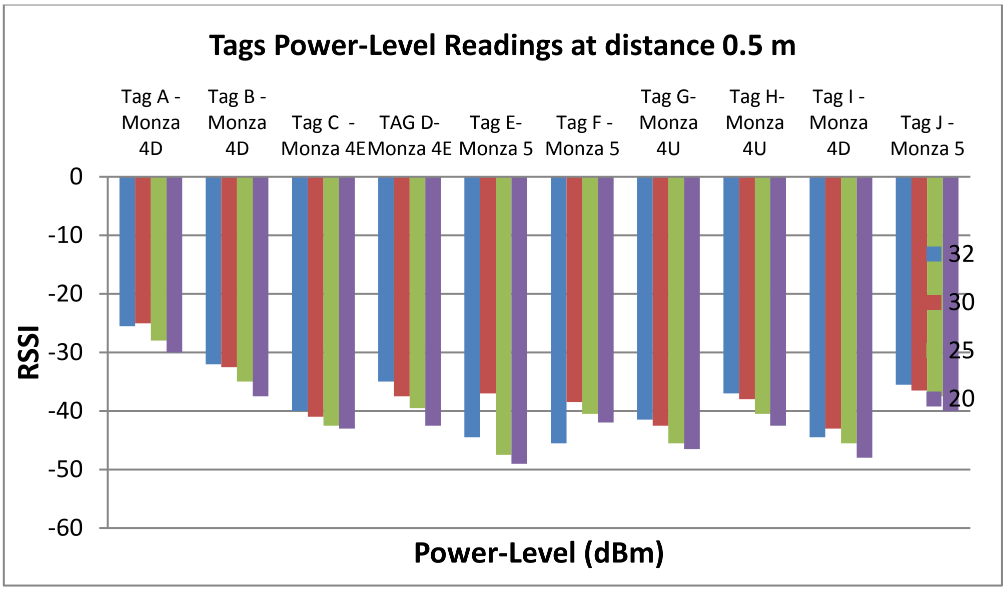

Figure 4.5. Tags Power Level Readings at a Distance of 0.5 m

From our experiments, we observed the following:

Tag A was performing reasonably well, except that at distances between 3.0 m and 3.5 m which the tag was not readable at lower power level values, 25 and 20 dBm. The tag did not respond well at a distance 3.9m yet showed the best RSSI readings of all the other tags. Tag B showed good performance within 3m. Tags C, D, E, F, and H responded similarly to Tag B in the power level experiment, except that Tag J was the most readable tag at 3.9m, compared to the other candidate tags. In summary, Tag A showed the best RSSI values over the other candidate tags even though it showed lower performance at certain dBm levels. Thus, Tag A was the most reliable tag in our power level experiment..

4.1.1.3 Tag Sensitivity Readings

This study measured the sensitivity of the various reader sensitivity levels at the maximum power level. This test helped us to understand which tag had the most sensitive characteristic from the sensing reader signals, and the experiment was important in determining the radiosensitivity behaviour of that tag.

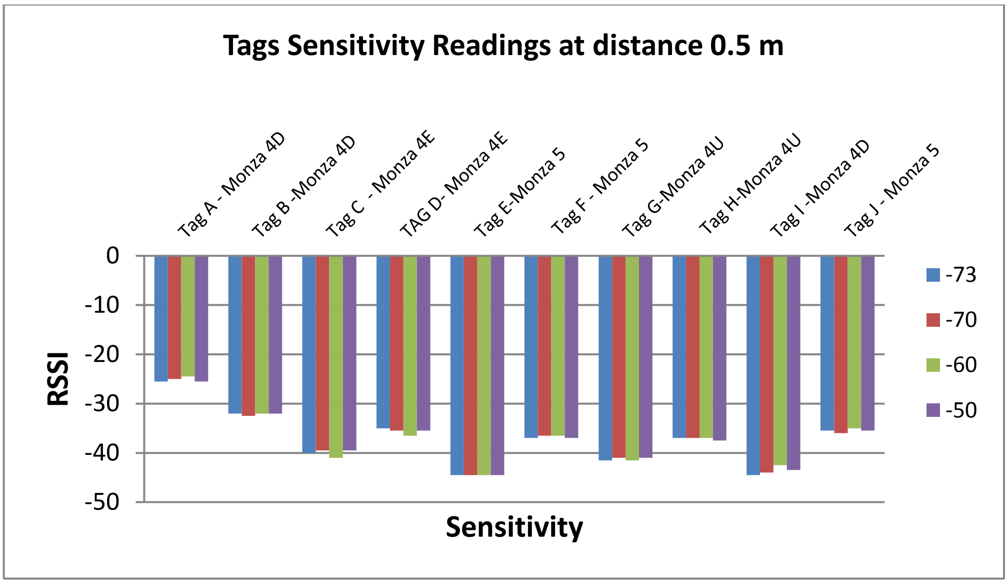

Figure 4.6.Tag Sensitivity Readings at a Distance of 0.5 m

According to the observations from the experiments, all tags performed well until a distance of 1.5 m, except for Tag B that did not report any RSSI readings. Tags E, F, G and H had not reported any readings at a distance of 2.0m, and that was due to the response factor of the tags' antenna and to the different sensitivity levels at different distances. At a distance of 3.5m, Tags A, I and J still reported RSSI values, while only Tag I reported RSSI readings at sensitivities (-73, – 70 and -50). In summary, tag sensitivity was determined in an inverse relationship between the tag position and sensitivity. The closer the tag was to the reader, the better the tag readings we noted. Based on overall performance, tag A recorded relatively good RSSI readings at various sensitivity levels compared to the other candidate tags, while Tag I was the most sensitive over all the other tags.

After analysing the three selection procedures, we noted tag A had the most desirable overall performance. Thus, tag A became our designated tag for localisation purposes. On the other hand, tags I and J showed distinctive, coveted features which would be useful for future localisation related experiments.

4.1.2 Antenna Calibration Procedures

An evaluation procedure was conducted to ensure consistent target tag behaviour over a set of tag distances and orientations facing each antenna. The evaluation stage was a benchmark in our localisation platform to evaluate the tag RSSI behavioural performance at various tag static positions and different target tag orientations from antennas. This procedure includes antenna high calibration and tag orientation - calibration evaluation.

4.1.2.1 RFID Antennas Height Calibration

It is important to defining the most appropriate calibration settings for the antennas. This required an antennas setup in an appropriate configuration in order to retrieve the maximum RSSI readings while sensing such RFID tags. We ran our program and tested the antenna performance at several heights 30, 50, 70, 80, 100 and 120cm respectively. The antennas returned superior RSSI readings at heights 30 cm and 50 cm respectively, as illustrated in Figure 4.7.

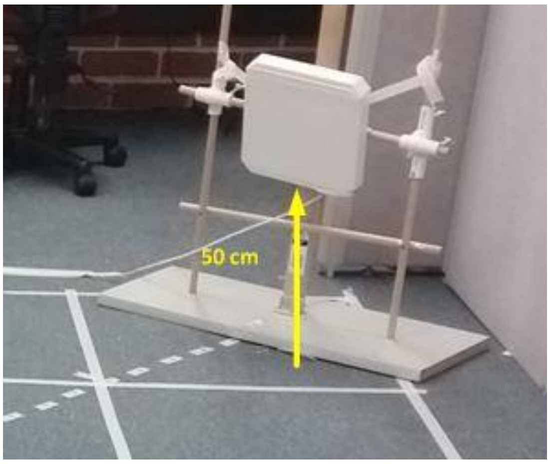

Figure 4.7. Antenna Height Calibration Setup

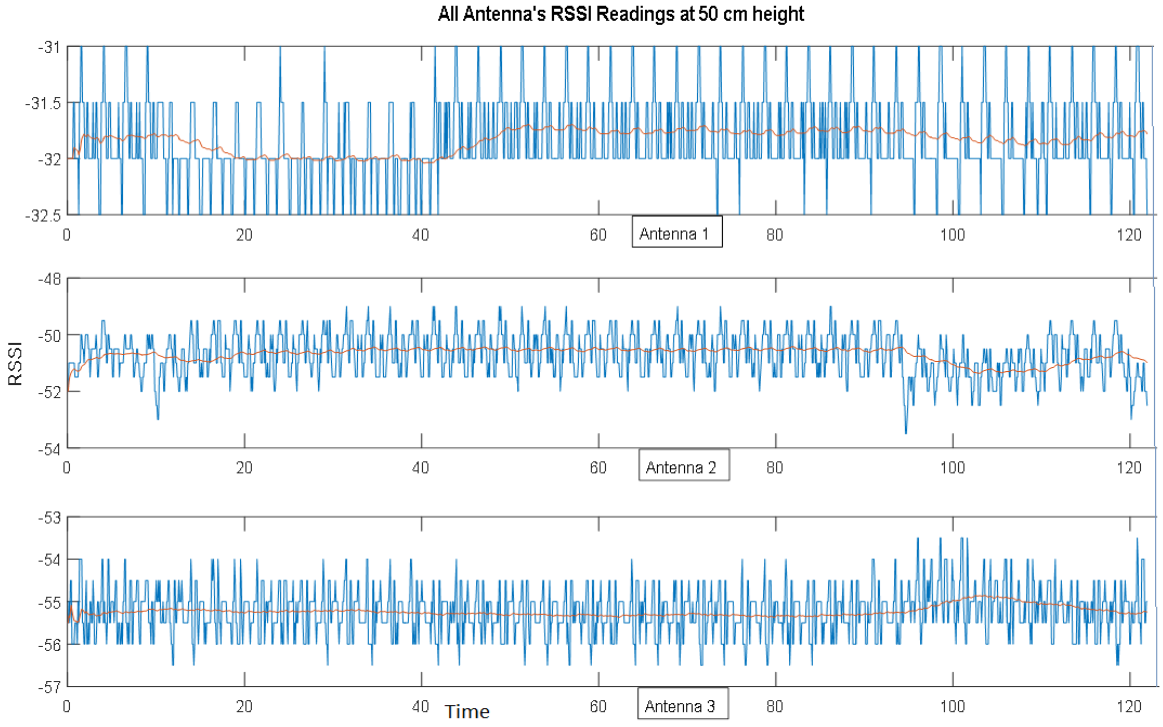

Figure 4.8. Antenna Readings at Height 50 cm

We noticed that Antenna 3 obtained lower RSSI values compare to Antennas 1 and 2. This could be because the power level emitted in the cable was subject to signal energy loss when we extended the connection cable to the RFID antenna coming from RFID reader. To overcome this problem, we increased the power value from the reader which was going throughout Antenna 3 cable at a maximum power level to enhance the performance of this Antenna. The recorded RSSI values of Anenna 3 remained lower than the readings from Antennas 1 and 2.

From the experiment, we observed that as we increased the height of the antennas, the RSSI readings starting to drop, which meant the higher the antenna, the lower the RSSI reading, and the lower the antenna, the better the RSSI reading. At a height of 50cm, our outcome coordinates were the closest to the actual tag location. Appendix A demonstrates further antenna height analysis at various antenna heights.

4.1.2.2 Tag A Orientation and Calibration

Tag A behaviour at static locations over periods of time.

In this experiment, we aim to evaluate the RSSI readings of the target tag A and the performance of each antenna at a point facing the target tag. We located tag A 50 cm away from the target antenna in a static location. Then, we ran the program for a short time, less than 8 seconds. We obtained the results illustrated in Figure 4.9:

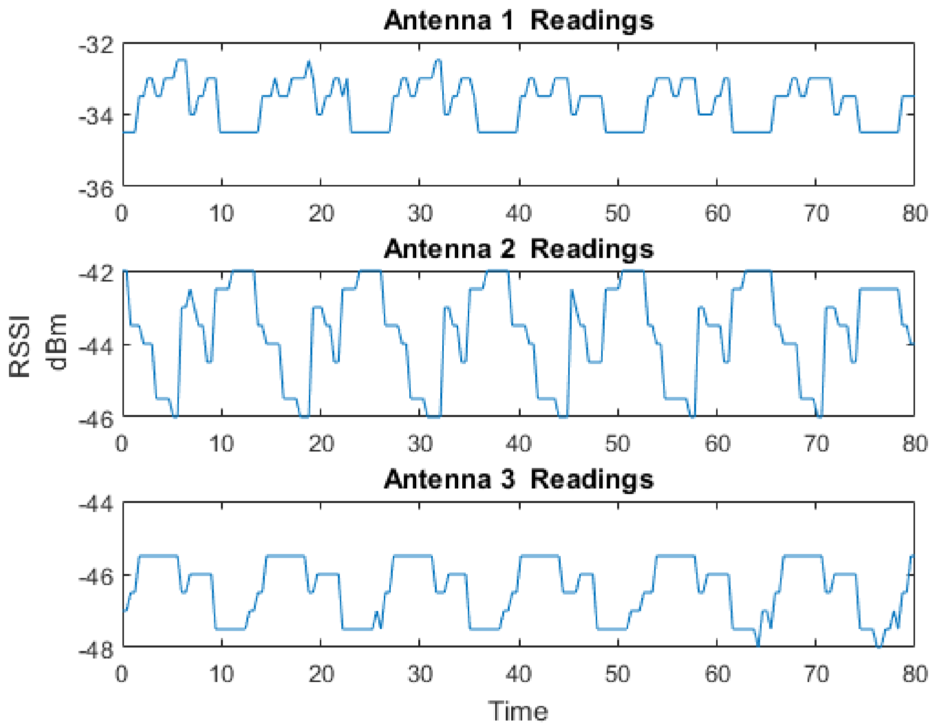

Figure 4.9 Tag orientation at static location (50 cm) of each antenna – 8 seconds

In this experiment, the results from the three antennas were obvious – the RSSI signals had steady patterns with similar features. Consequently, we concluded that that RSSI values did not change significantly at stationary locations. This helped us to understand the nature of RSSI

In the second test, we performed orientation of tag A a longer time, five minute intervals, moving the tag 10 cm each time, starting at 50 cm up to 150 cm, with the tag facing Antenna 1. We obtained the results illustrated in Figure 4.10:

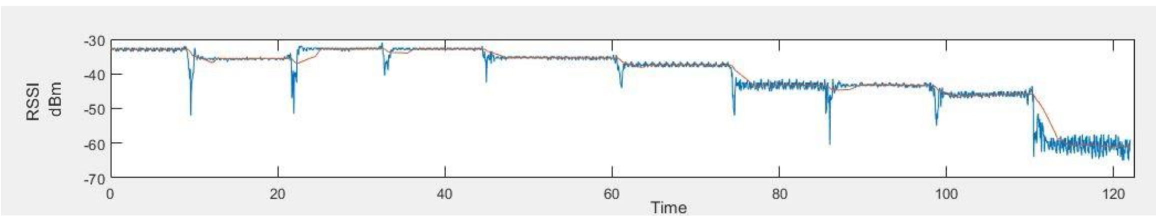

Figure 4.10 tag A facing Antenna 1 over 5 minutes run-time

From the experiment, we noticed that the performance of the tag was relatively stable until the readings started to drop from 60 points after 100cm, as can be seen in Figure 4.10. Based on our observation, the further the tag was moved over a period of time, the lower the RSSI values we obtained. As seen in Figure 4.10, because of the human interference caused when picking up tag A to move it to a new position, irregular readings were reported. In this experiment, we intended to evaluate the performance of tag A over a longer timeframe, where the run time was over 5 minutes. The overall performance indicated that tag A was suitable for a reasonable period of run time (5 minutes). Further, the RSSI readings were reliant on the tag orientation and tag distance.

Tag A orientation calibration at various distances from target antenna

The tag orientation test was a crucial step to determine the performance of the target tag and the power level received from the tag to evaluate its functionality for localisation purposes.

This test evaluated the behaviour of each antenna from different tag A positions. In the beginning, we executed this experiment when the tag was facing each antenna at a distance of 10 cm (see Figure 4.11). We evaluated the performance of each antenna by running the Java program for two minutes with the following results:

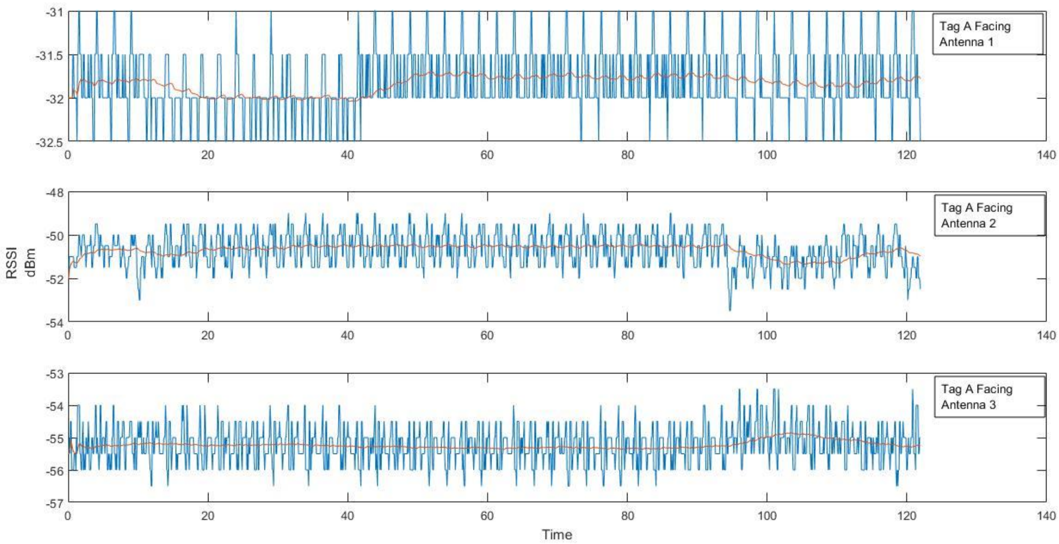

Figure 4.11 Test A facing Antenna 1

The experiments showed that the orientation of the tag had a significant impact on the RSSI values. In other words, if the tag directly faced the antenna, it gave hight RSSI values. When the tag's reverse side was facing behind the antenna, it gave relatively good RSSI readings which were reported by the back side of the other antenna. Thus, each time tag A was facing a specific antenna, it reported stable RSSI values, while other antennas reported lower values and fluctuations in RSSI readings if tag A was not facing the antenna. This led us to understand that the antenna reported different RSSI values each time, based on the orientation of the tag.

To examine the orientations of tag A, we extended the experiments by moving tag A 30 cm away from Antenna 1 each time, (see Appendix A). According to the results, we observed that tag A performed well and gained desirable RSSI readings when it was facing Antenna 1 with distances between 30 cm and 180 cm. This showed that tag A had better RSSI values when it's orientation and distance were not too close to, or too far from the antenna. This led us to understand that at any distance between 30 cm to 180 cm from Antenna 1, tag A recorded the best RSSI values and thus, the optimal location accuracy.

4.1.2.3 Neighbour Tags Influence in Target Tag

Passive RFID signals (RSSI) are impacted by interference from their surrounding environment. We assumed that tag A would be influenced by its neighbouring tags so we decided to run those tags for 8 minute running times to evaluate tag A's performance (see Figure 4.12) and Appendix A for further analysis.

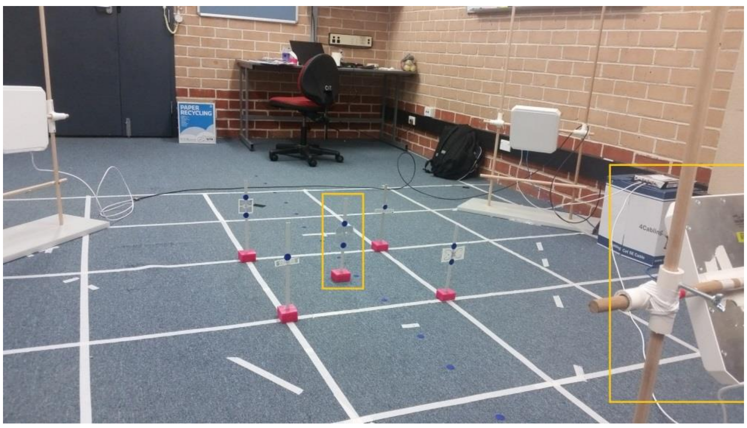

Figure 4.12 Neighbouring tags test with target tag A (indicated by small yellow box) facing Antenna 1 (indicated by large yellow box)

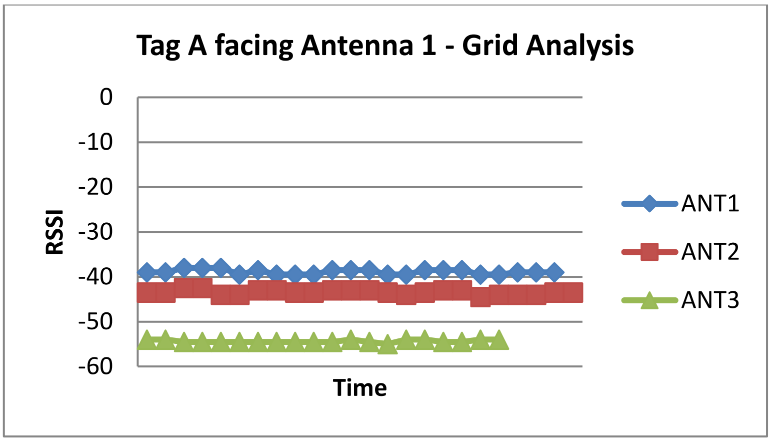

Figure 4.13 tag A facing Antenna 1 - neighbouring tag analysis

From the experiments, we observed that the RSSI readings were stable when tag A was facing each antenna at static locations and we did not observe any significant changes in RSSI values when there were nearby passive RFID tags. Thus, our assumptions were justified.

We concluded from the tag and antenna orientation experiment that the best antenna height was at approximately 50 cm, and there was no significant changes in RSSI during calibration experiments. Eventually, neighbour tag has so direct influence on target tag for localisation process.

4.2 Localisation Results

In this section, we present the localisation procedures, steps and experimental results from the evaluation of our proposed localisation framework using only one target tag, i.e. tag A. Our localisation framework aimed to improve the accuracy of location estimation by deploying only one affixed tag. Localisation experiments were necessary to approve our system to ensure their role in improving personal healthcare monitoring systems in Smart Homes. By understanding the target locations for related health assistance such as personal health via daily living activities using cost-effective localisation technique. The localisation experiments were conducted through systematic steps which are described in the following subsection.

4.2.1 Distance Measurement

To determine the location of the target tag, it was important to know the distance of the subject referring to the node (RFID Antenna). Finding the best position for the target tag was reliant on knowing the coordinates of the other tags and where they were located on our localisation platform grid. In the tag selection procedure (tag readings at different distances), there was a strong relationship between the tag RSSI values and the tag distance at a specific time. If the distance increased, the tag's RSSI reading decreased. Based on our observations of tag behaviour during the selection procedure, we plotted the tags RSSI readings against the distance of all other tags. tag A showed the most outstanding RSSI values over different distances from the RFID reader (see Figure 4.14). Therefore, we carried out another experiment to understand the relationship between RSSI and distance so that we could derive a distance formula.

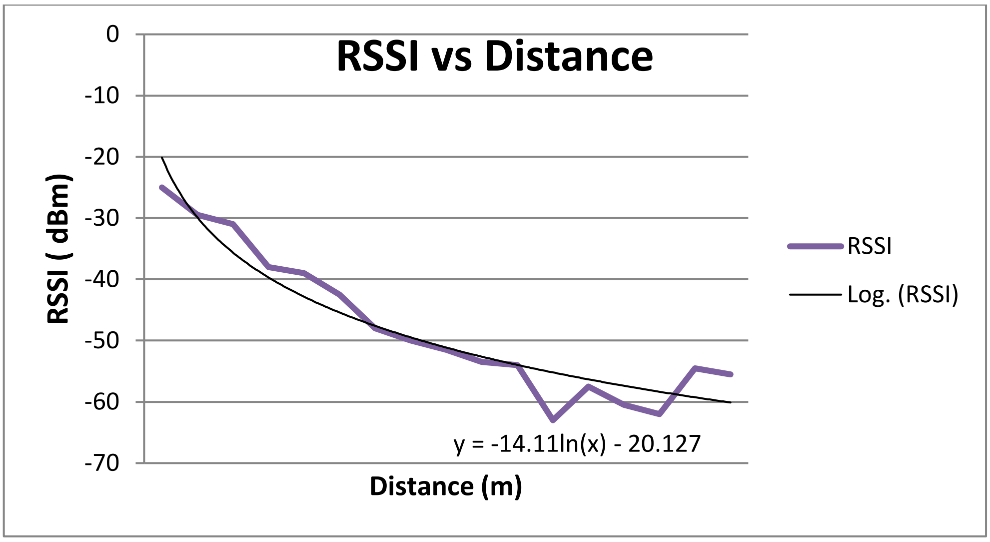

Figure 4.14. Distance vs. RSSI for tag A

By using the logarithm trendline, we extracted the following equation by converting RSSI to distance:

$$D = -14.11ln(x) - 20.127$$

where D is the distance of a tag at a certain position.

The above formula was the key to calculate the distance of each tag and to determine which tag would be used in later experiments, using the geometry algorithms. The extracted distance formula is almost the same as the theatrical distance formula in equation (5) [115].

4.2.2 Smoothing RSSI Readings

The fluctuations in RSSI values led to uncertainty in location estimation. Typically, RSSI signals are easily interferred with by environmental factors and other influences that lead to multi-pathing and increase the error in location estimation. To smooth RSSI readings and reduce the noise in the RSSI signal, we decided to use appropriate, efficient smoothing filters such as the moving average filter. The average moving filtering experiment illustrated that RSSI values were smoothed plainly as shown in Figure 4.15.

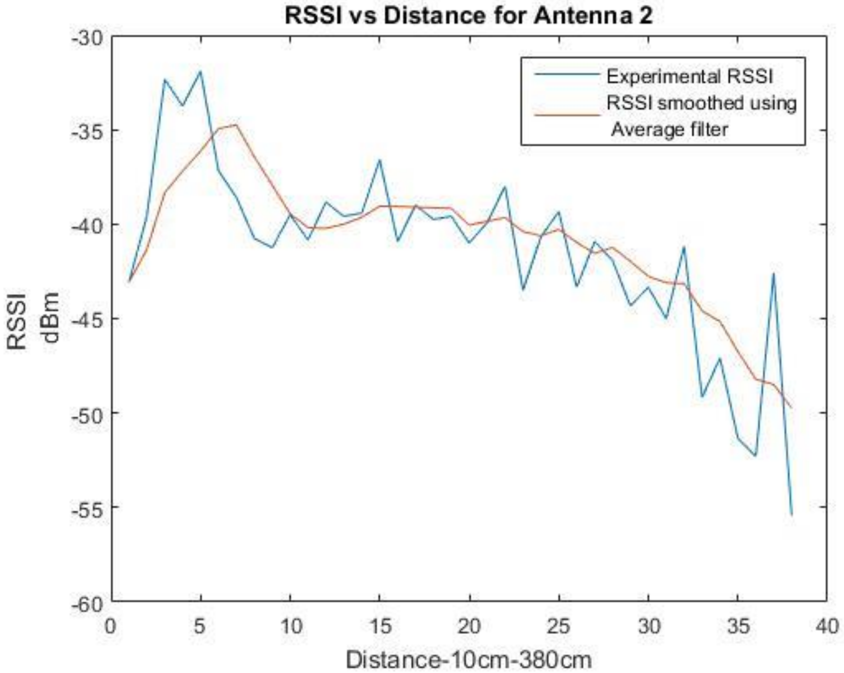

Figure 4.15. Showing filtered RSSI values for Antenna 2 using average moving filter

4.2.3 Localisation Experimental Results

4.2.3.1 Localisation Trilateration Results in Stationary

To determine the appropriate location of an affixed target tag, it was essential to determine the location of the individual. To evaluate the most appropriate results for localising passive tag A, we evaluated our system at stationary settings, where tag A was replaced in our platform (see hardware setup, Section 3.2.1), at different static locations, facing all antennas at different angles from each antenna. The results represent tag A positions at several locations in the grid floor in our localisation platform (See Table B. 1 for further details in Appendix B). These experiments were vital to learn the locations of the tags at several static locations. This knowledge was used for determining the location of tag A at movable locations.

To communicate and retrieve RSSI values for further distance calculations, we implemented a prototype in Java and applied a suitable localisation algorithm. We developed Java GUI (see Figure 4.16) to examine the performance of the target tag A. The graphical interface simulated our real localisation platform, where each grid represented several coordinates. Each coordinate represented an *X*- position and *Y*- position.

To locate the target tag and estimated locations, it was necessary to know the coordinates of each tag on the floor. We applied the distance formula to calculate tag distances (d_1, d_2 and d_3) of tag A in relation to each antenna, We then applied the geometry trilateration algorithm to estimate the target tag position *(X, Y).* We conducted several sub-experiments to draw an accuracy map for our localisation platform from static locations. The results are illustrated in Figure 4.17.

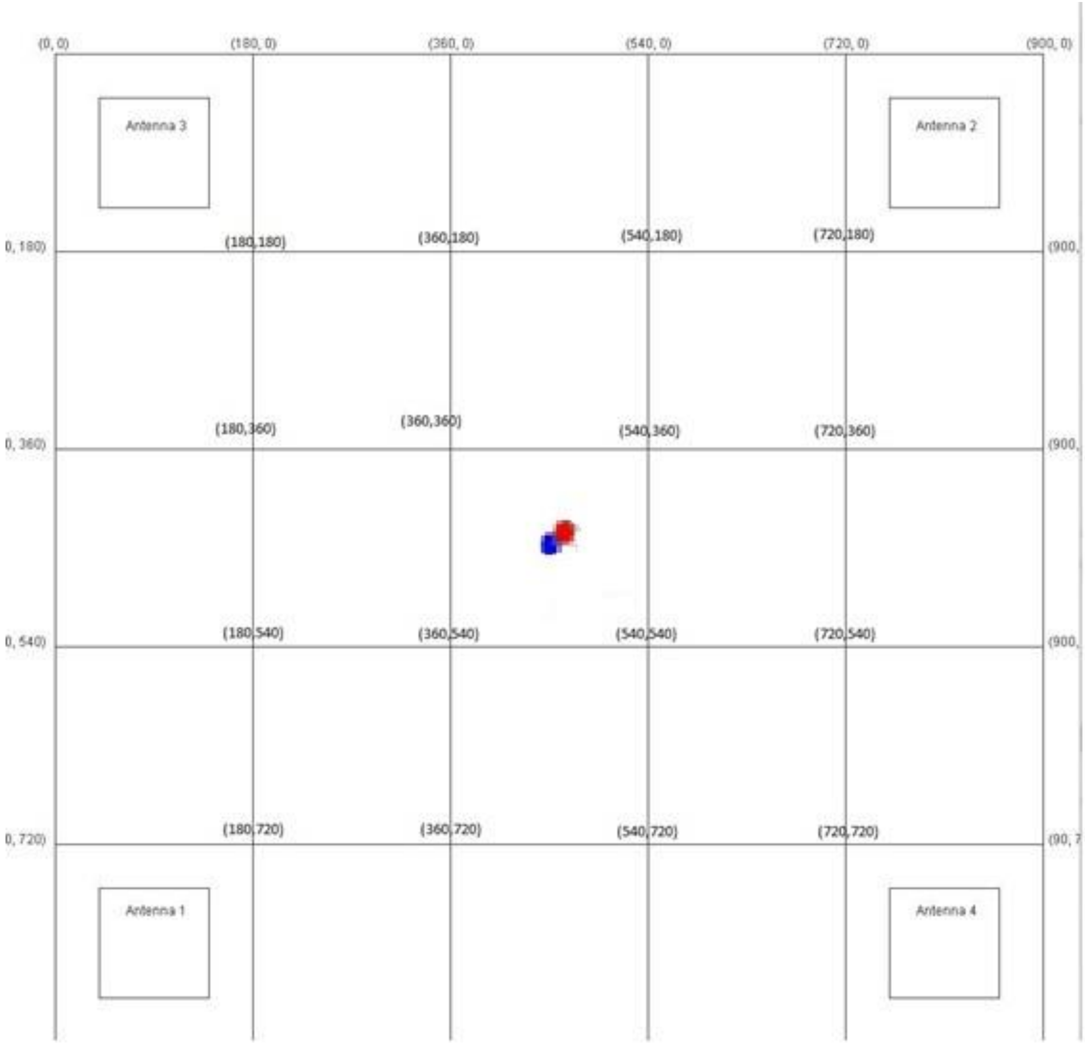

Figure 4.16 The figure shows tag A estimated location in comparison to actual location at coordinates (X-450, Y-450 or centre point). See Table B. 1 for localisation comparison results between original coordinate and estimated position in Java GUI.

The above figure illustrates the actual location tag A with a blue dot, while the estimated location is represented by a red dot. Appendix (B) shows the original actual coordinates drawn in our localisation platform. The estimated location (red dot) comparing the actual location in the blue dot. The experiments estimate the position of tag A compared to the actual location in stationary settings ,which also shows the accuracy percentage of each estimated location in relation to the actual position. The accuracy percentage represented by following:

First, we calculate the distance error (€) between actual position (X, Y) and estimated position ($X_{calculated}$, $Y_{calculated}$) as following:

$€ = \sqrt{(X - \text{X calculated })^2 + (\text{Y} - \text{ Ycalculated })^2}$

Then we calculated accuracy as following:

Accuracy = $(\frac{(1-€\ )}{platform\ area\ size}) * 100$

We overlaid our platform with a grid consisting of several coordinates represented by actual locations (see Figure 4.16). Each time we placed tag A at a known static position on the floor, we ran our Java program.

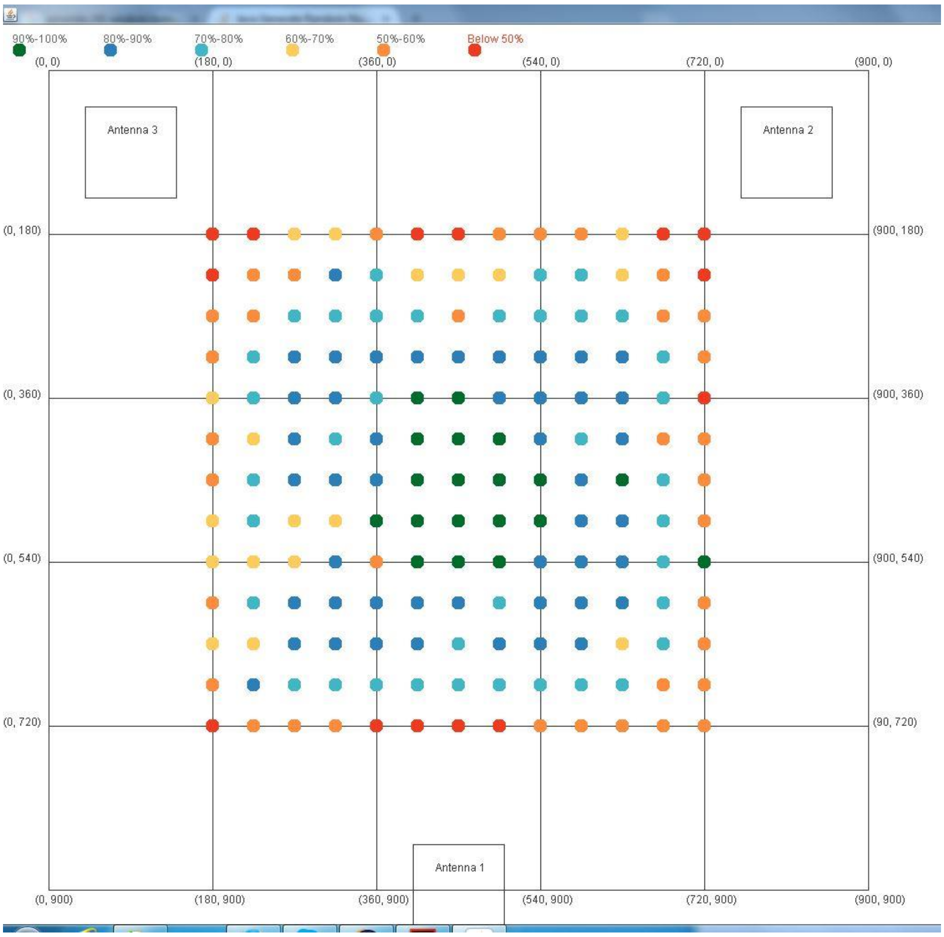

Figure 4.17. Accuracy map of the estimated locations of tag A at several positions using the trilateration algorithm in our localisation software using Java API

We conducted our experiment to determine the accuracy of our localisation platform. Tag A positions were at various points, mostly within the central area of the grid as shown in Figure 4.17. The figure also illustrates the average performance in accuracy percentage of the target tag A at different positions. The results indicated that high accuracy points were located at the central area of the grid. Each colour represents a different accuracy level. For instance, green dots represent the average accuracy above 90% with (mean M = 94.27%, standard deviation SD = 2.08%). With an average error of 16.5 cm, the highest accuracy recorded was 98% which is represented by the centre point of the grid in the localization platform (less than 2 cm of error). Dark blue dots are located in the outer centre of the grid - 80% to 90% recorded accuracy with (M = 84.81%, SD = 2.81%) and 70% to 80% (M = 76.45%, SD = 2.83%) respectively. Yellow, orange and red dots showed the lower accuracy percentages (60% to 70%, 50% to 60% and below 50% respectively). These dots were located at the outer of the centre grid.

According to these results, our system indicated that there were some limitations. For example, the red dots at the far outer areas represented the lowest accuracy we obtained. Moreover, our system recorded blinds spots. These blind spots were closer to the antennas and our platform boundaries. In fact, we observed that RSSI change rapidly or even become unreadable at times due to the lower antenna coverage at those spots. Further, our localisation algorithm required tag location coordinates in order to calculate the actual location in order to obtain a relatively acceptable accuracy rate. For more details on trilateration experiments see Table B. 1 in Appendix B.

4.2.3.2 Localisation Multilateration Results in Stationary

We added a fourth antenna to our localisation platform, as it was important to know which algorithm would work more efficiently in our developed localisation platform. Hence, we found that using other interesting geometry localisation algorithms such as multilaterion would help us to calculate the distances (d) from all four antennas. Multilaterion determined the distances from multiple nodes, after which we applied the calculation to find the location of the target tag based on the distance the tag generated from each node (RFID Antenna). We made a few changes in our localisation platform once we added the fourth antenna. Further, we adjusted our localisation protoype with no changes in Java GUI original coordinates, and we added the fourth antenna in the graphical settings as well as our physical platform configurations (see Figure 4.16).

We decided to use the fourth antenna in order to optimise the accuracy results of the target tag A, and to investigate whether adding extra resources would be valuable based on our first results from the trilateration (three antennas). In a similar fashion to trilateration, we performed extensive experiments to evaluate multilateration in stationary settings in our localization platform. The results of our experiments using four antennas and multilateration algorithm are illustrated in Tables (Appendix B, Tables B.2 to B.5).

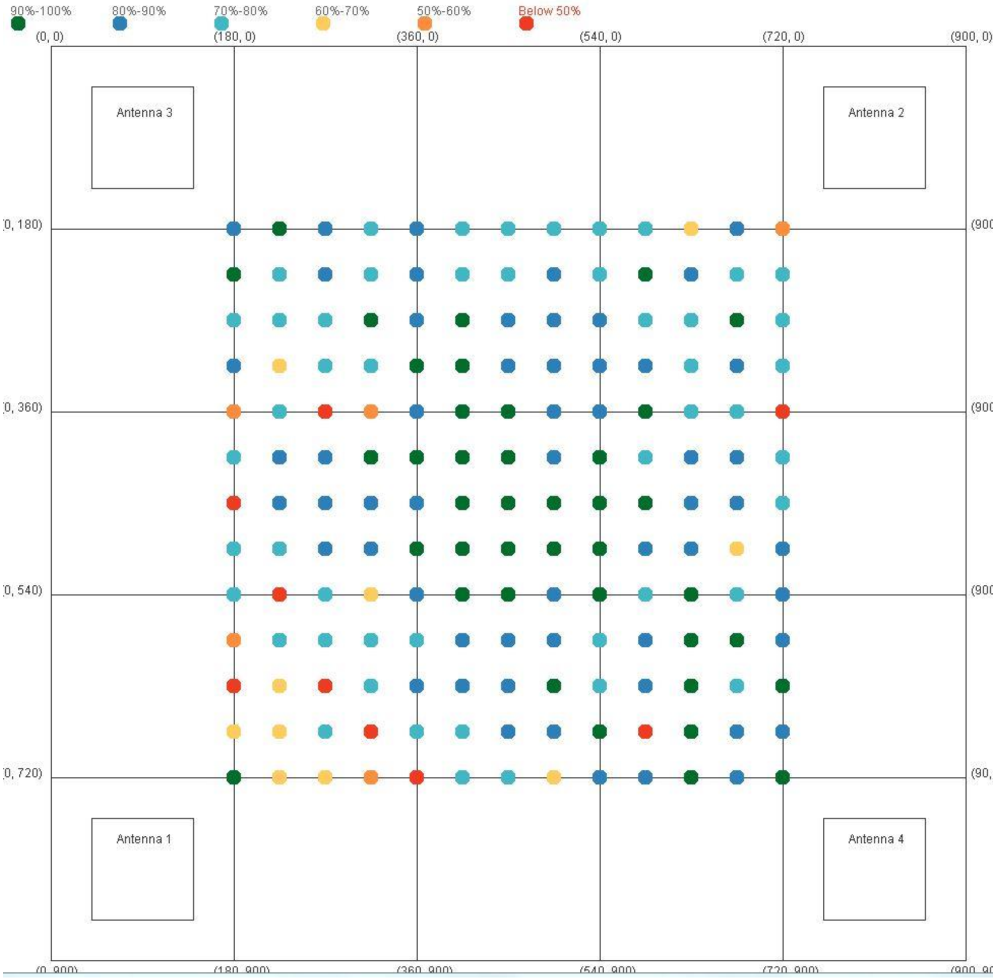

Figure 4.18. Accuracy map of the tag A estimated locations at several positions using multilateration algorithm

Figure 4.18 illustrates the average performance in accuracy percentage for tag A in various positions of our localisation platform. According to the recorded results, the overall performance was improved by using four antennas and the multilateration algorithm. For example, green dots (90% with mean, M = 93.5% and standard deviation, SD = 2.88%), with an average error of 19.45 cm. The highest accuracy was recorded with a 1 cm error at the centre grid, illustrated by dark blue (80% - 90%, M = 84.64%, SD = 3.01%) and sky blue dots (70% - 80%, M = 75.37%, SD = 2.77%) respectively. These more apparent in the accuracy map distribution and which is taking over the less accurate dots (Orange, Yellow and Red), comparing to accuracy results from trilateration accuracy map (see Figure 4.17).

Outside the central area of the grid, a clear improvement can be seen in accuracy levels at different position in our platform using multilateration and four antennas compared to the previous results in Figure 4.17. Note that the blind spots were not examined in the multilateration experiments because our goal was to improve the accuracy map compared to the previous experiments. For more details on multilateration experiments see Table B. 2 to Table B. 5 in Appendix B.

Comparing the results achieved by both techniques, trilateration showed better average accuracy in the central area while multilateration showed better accuracy overall.

During our stationary experiments, we noticed that tag orientation had a significant role in improving the RSSI readings. Further, we found that the angle of arrival, or phase angle, in between the tag and the antenna, had a significant impact on RSSI values. For instance, if the tag setting on the floor was where the tag A sensor was not facing the RFID antenna, the recorded RSSI of that antenna was lower than when the tag faced a certain antenna. Thus, it is important to investigate further the tag disposal to understand tag response during the localisation process in various orientations.

4.2.3.3 Localising Movable Object

In our scenario, we intended to test the accuracy of localising an elderly person's movements in a Smart Home space. Tracking the movement of a person in a Smart Home environment is the key to successful outcomes in personal health monitoring. In order to recognise their activities in an indoor environment it is essential to use the appropriate activity recognition module. To evaluate our system in real-world scenarios, we decided to track tag A affixed to a moving walking stick that was carried by an individual. Our goal was to see how the human body interference affected the target tag's RSSI readings and how that would reflect in the accuracy of the results. Our scenario was non-interventional to the human body, which meant the human was not required to wear the tags on their body. We evaluated the scenario by running experiments to determine the accuracy level in the centre of the localisation platform and the grids around the centre grid. A graph depicting the results is illustrated in Figure 4.19.

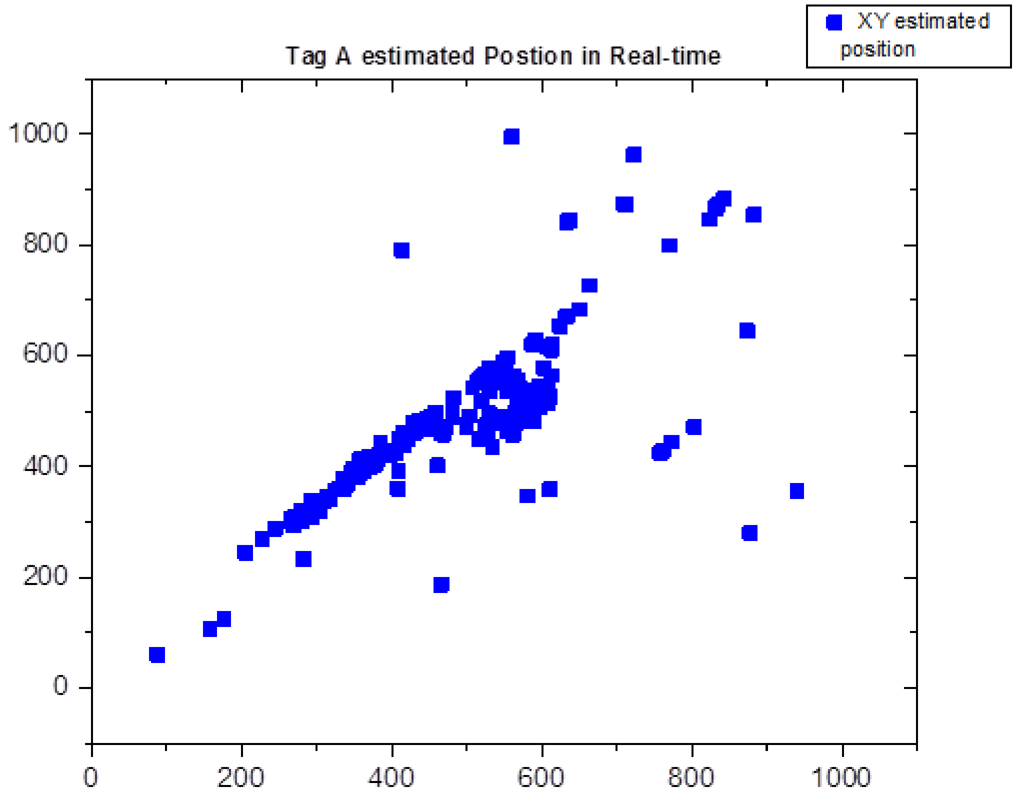

Figure 4.19. Tag A - estimated locations density distribution in real-time tracking in our localisation platform

In the experiment, a volunteer carried the walking stick with tag A affixed to it and walked around the centre area of the platform. The data collected from experiments were in 30 second timeframes. According to Figure 4.19, the results show that the tag A position estimations were higher at the centre of our localisation platform (X,Y positions in-between 400 and 600 in the grids), but when the person moved slightly from the centre area, the accuracy in estimated location dropped. Also, the graph shows some irregular estimated positions (900 or above), which do not represent any location inside the localisation platform. This is due to the fact that when a person moved faster or changed their direction suddenly, or blocked tag A from the antenna, the results were poor.

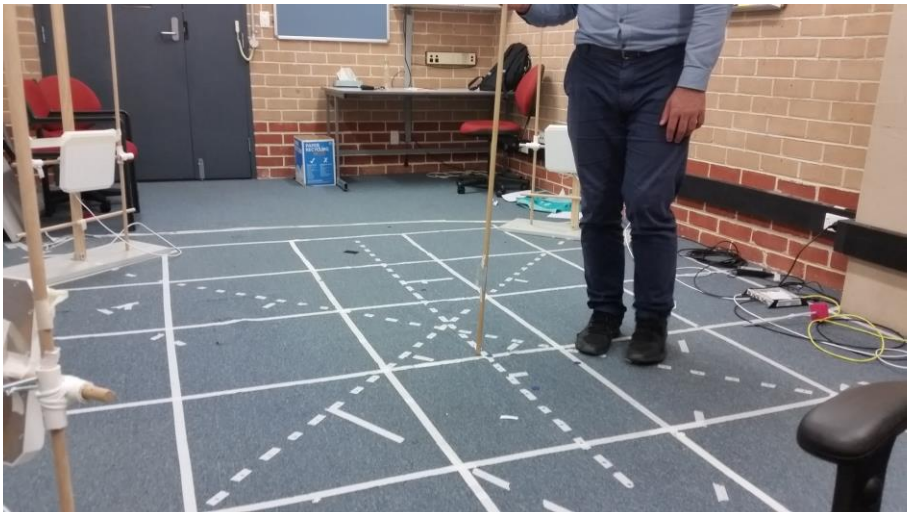

Figure 4.20. Tag A - attached to with walking stick carried by volunteer who is inside the localisation platform

In the experiment, we noticed that when the person moved away from the centre grid, the estimated positions of tag A dropped significantly, when the tag was closer to blind spots. Further, we observed that tag orientation during real-time localisation had another substantial role in determining a positive estimate of the tag location. For instance, when tag A was facing an antenna, then the estimated position of tag A created a better RSSI value. In summary, tag localisation in real-time reported promising results in location awareness of tracking a moving individual. Nevertheless, further research is needed to address localising a movable tag in a real environment with human body interference. Moreover, another method is required to study real-time localisation using only a single target tag.

4.3 DISCUSSION

Observing from trilateration experimental tests, low accuracy results were recorded outside central area as well as the blind spots (see Figure 4.17). We found that when localisation configuration consists of only three antennas in a triangular format, this configuration can create blind spots, e.g. the areas that are not covered by antennas. The orientation of the tags and the antennas also plays a significant role in the accuracy outputs. The trilateration configuration only uses one passive tag so that the orientation of the tag affects significantly the RSSI readings. Results showed that the relationship between RSSI and AoA (Angle of Arrival) varies significantly during the measurement. The results indicate that the RSSI reading gets its peak performance when the tag is facing directly towards the corresponding antenna (i.e. AoA is 0° or 180°). When the tag is facing the antenna's sideways, the reading decreased dramatically. This suggested that this type system is suitable for operations that track subjects within the area of 1.10m × 1.20m. Despite the challenges that we faced during the experiments, our proposed framework was able successfully to track subjects' movement. We applied a RFID tag on a walking stick in the space of 60cm × 60cm. A person is acting as an elder and moving the walking stick slowly in the area. We visualized the movements and determined its accuracy. Results suggested that the accuracy is still over 90% in the central area, even with human and objects interferences. However, there were a few spikes during the experiment. This could be resulted by the sudden change of movement from the person moving the walking stick. The experiment positively shows that our system performs well with high accuracy in the central and near central areas. Reasonably good results were achieved considering the simplicity of our system that uses minimal tracking resources: three antennas and one "almost nil cost" passive RFID tag.

Similarly, in *Multilateration* experiments, we noticed that the tag orientation had a significant role in improving the RSSI readings. We found that the angle of arrival, or phase angle, in between the tag and the antenna, had a significant impact on RSSI values. As we face the tag directly towards an Antenna, we receive the best reading from that corresponding Antenna. However, the readings from the sides are not good. This also explains that why we have bad accuracy at the outer circle of the grid. The positioning of the tag is not great at those points, the vertical and horizontal orientation of the tag from each reader affects the RSSI readings greatly. Altough we got average accuracy of 19.45 cm in the centre of the platform, the overall accuracy results outside centre grid it has significantly improved (see Figure 4.18). Since *Multilateration* requires four distance readings in order to derive the actual location, if we get an inaccurate reading from one of the Antennas, it will lead to inaccurate position estimation. Thus, it is important to investigate further the tag disposal to understand tag response during the localisation process in various orientations.

We have validated our hypothesis in real experiments and we have received promising results in both trilateration and multilateration in comparison with the existing systems. We also carried out a successful tracking experiment that used one passive RFID tag which was attached to an assistive walking tool. It did not require the individual person to wear it or attach the tag to his/her body. In addition, by using passive tag, our system does not need frequent maintenance and bucky items compared to the active tags that use of the battery.

5 CONCLUSION AND FUTURE WORK

5.1 Conclusion

The key contributions of of each chapter are summarised as follows:

In chapter two, we carried an extensive survey on Smart Homes and Smart Homes healthcare projects from which we identified the challenges in Smart Homes healthcare. We also discussed indoor localisation and technologies in Smart Homes in this chapter with a comprehensive summary of RFID indoor tracking techniques and the estimated location accuracy levels of the previous research works.

In chapter three we proposed a localisation framework using passive RFID-based technology to localise affixed tags to objects in stationary settings and in real time. We designed and developed our localisation platform in a cost-effective way by using a minimal number of tracking resources, yet we obtained desirable results in accuracy within stationary settings. The localisation framework was divided into three stages. The first stage was to select the suitable passive tag through set of tag selection procedures such tag selection based on RSSI reading range, tag selection based on power reading level, and tag sensitivity selection. Tag calibration in second stage, was carried to evaluate the performance of the selected tag from the previous selection stage. The performance evaluation includes tag performance at different directions of the passive RFID antenna and tag orientation. In the last stage, an appropriate passive RFID localisation technique was implemented to optimise the accuracy of the localisation works.

In the following chapter, we developed a physical localisation platform to verify our theoretical localisation framework, and test the effectiveness and the efficiency of the new approach. To evaluate our framework, we built a hardware platform based on passive RFID technology using speedway revolution R420 kit from Impinj technologies. Also, we developed a prototype that used Java to retrieve RSSI values from target tags for further analysis, as well as devised distance measurements and applied localisation algorithms. The experimental results showed that our system was able to achieve a desirable accuracy levels in stationary scenarios for both trilateration and multilateration with average of16.5 cm and 19.45 cm respectively (see Table B. 1 and Tables B. 2- B.5 in Appendix B for details). We believe that our localisation system has a potential in various indoor localisation applications including healthcare, such as tracking elderly people, human activity recognition and others.

5.2 Future Work

With the limited timeframe and the scope of this thesis, a limited evaluation procedures and experiments were carried out the laboratory environment. Further research in indoor localisation is required to improve passive tag localisation in RFID-based systems, especially in using Kalman filter and Particle filter to estimate affixed tag on movable subjects (such as human).

An important factor in tag orientation procedure is to examine the candidate tags under multiple reader placements and various configurations. Within the limitation of this thesis, we only evaluated the tag orientation once which the target tag is facing each antenna at several heights. The tag orientation could improve the tag RSSI readings performance if the tag performance was investigated at different angles in relation to each antenna, and with variations in tag placement.

Another potential improvement may be revealed by studying target tag localisation at various AOA and evaluating the system performance while considering the most suitable algorithms. During our experiments, we noticed that the phase of angle had an impact on RSSI values, and a suitable angle would improve the performance of the localisation.

In our system, we evaluated the distance measurement after tags RSSI was filtered using moving average filter algorithm. Applying further RSSI signal and location estimation filterings could improve the overall accuracy. This could be achieved by optimising the experimental results using the suitable RSSI filters.

The future work will also apply RFID technologies to tracking basic daily tasks in Smart Homes for healthcare and wellbeing, such as ironing, dressing or washing dishes. It is important to investigating suitable human activity recognition algorithms and machine learning techniques such as supervised, semi-supervised or unsupervised to optimise the accuracy in recognition the activities. This includes the differentiation of basic and concrete activities of daily living.

PUBLICATIONS

Alsinglawi B, Liu T, Nguyen QV, Gunawardana U, Maeder AJ, Simoff S. Passive RFID Localisation Framework in Smart Homes Healthcare Settings. In: al AJMe, editor. The Promise of New Technologies in an Age of New Health Challenges: IOS Press; 2016. p.p. 1-8 (received best student paper award).

Alsinglawi B, Elkhodr M, Nguyen QV, Gunawardana U, Maeder AJ, Simoff S. RFID Localisation for Internet of Things Smart Homes: A Survey. International Journal of Computer Networks & Communications (IJCNC); 9(1); 2016, pp. 81-99.

Alsinglawi B, Nguyen QV, Gunawardana U, Maeder AJ, Simoff S. RFID Systems in Healthcare Settings and Activity of Daily Living in Smart Homes: A Review. E-Health Telecommunication Systems and Networks, 6(1), Scientific Research Publishing; 2017, pp.1-17.

BILIOGRAPHY

[1] T. Sanpechuda and L. Kovavisaruch, "A review of RFID localization: Applications and techniques," in *Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 2008. ECTI-CON 2008. 5th International Conference on*, 2008, pp. 769-772.

[2] Y. Zhao and J. R. Smith, "A battery-free rfid-based indoor acoustic localization platform," in *IEEE International Conference on RFID*, 2013, pp. 110-117.

[3] G.-y. Jin, X.-y. Lu, and M.-S. Park, "An indoor localization mechanism using active RFID tag," in *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing*, 2006, p. 4 pp.

[4] A. Kotanen, M. Hännikäinen, H. Leppäkoski, and T. D. Hämäläinen, "Experiments on local positioning with Bluetooth," in *Information Technology: Coding and Computing [Computers and Communications], 2003. Proceedings. ITCC 2003. International Conference on*, 2003, pp. 297-303.

[5] Z. Alliance, "IEEE 802.15. 4, ZigBee standard," *On* http://www*. zigbee. org,* 2009.

[6] T. Gigl, G. J. Janssen, V. Dizdarević, K. Witrisal, and Z. Irahhauten, "Analysis of a UWB indoor positioning system based on received signal strength," in *Positioning, Navigation and Communication, 2007. WPNC'07. 4th Workshop on*, 2007, pp. 97-101.

[7] E. Aitenbichler and M. Mühlhäuser, "An IR local positioning system for smart items and devices," in *Distributed Computing Systems Workshops, 2003. Proceedings. 23rd International Conference on*, 2003, pp. 334-339.

[8] L. Hu, D. M. Ong, X. Zhu, Q. Liu, and E. Song, "Enabling RFID technology for healthcare: application, architecture, and challenges," *Telecommunication Systems,* vol. 58, pp. 259-271, 2015.

[9] S.-C. Kim, Y.-S. Jeong, and S.-O. Park, "RFID-based indoor location tracking to ensure the safety of the elderly in smart home environments," *Personal and ubiquitous computing,* vol. 17, pp. 1699-1707, 2013.

[10] G. P. Joshi, S. Acharya, C.-S. Kim, B.-S. Kim, and S. W. Kim, "Smart solutions in elderly care facilities with RFID system and its integration with wireless sensor networks," *International Journal of Distributed Sensor Networks,* vol. 2014, 2014.

[11] A. Coronato, *Pervasive and Smart Technologies for Healthcare: Ubiquitous Methodologies and Tools: Ubiquitous Methodologies and Tools*: IGI Global, 2010.

[12] L. Yao, Q. Z. Sheng, W. Ruan, T. Gu, X. Li, N. Falkner*, et al.*, "Rf-care: Device-free posture recognition for elderly people using a passive rfid tag array," in *proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services on 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, 2015, pp. 120-129.

[13] D. Zhang, F. Xia, Z. Yang, L. Yao, and W. Zhao, "Localization technologies for indoor human tracking," in *Future Information Technology (FutureTech), 2010 5th International Conference on*, 2010, pp. 1-6.

[14] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems (TOIS),* vol. 10, pp. 91-102, 1992.

[15] J. Wan, M. J. O'grady, and G. M. O'hare, "Dynamic sensor event segmentation for real-time activity recognition in a smart home context," *Personal and Ubiquitous Computing,* vol. 19, pp. 287-301, 2015.

[16] M. Amiribesheli, A. Benmansour, and A. Bouchachia, "A review of smart homes in healthcare," *Journal of Ambient Intelligence and Humanized Computing,* vol. 6, pp. 495-517, 2015.
[17] N. Noury, G. Virone, P. Barralon, J. Ye, V. Rialle, and J. Demongeot, "New trends in health smart homes," in *Enterprise Networking and Computing in Healthcare Industry, 2003. Healthcom 2003. Proceedings. 5th International Workshop on*, 2003, pp. 118-127.
[18] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes—Present state and future challenges," *Computer Methods and Programs in Biomedicine,* vol. 91, pp. 55-81, 7// 2008.
[19] M. J. Rantz, M. Skubic, R. J. Koopman, L. Phillips, G. L. Alexander, S. J. Miller*, et al.*, "Using sensor networks to detect urinary tract infections in older adults," in *e-Health Networking Applications and Services (Healthcom), 2011 13th IEEE International Conference on*, 2011, pp. 142-149.
[20] P. Rashidi and D. J. Cook, "Keeping the resident in the loop: Adapting the smart home to the user," *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on,* vol. 39, pp. 949-959, 2009.
[21] D. J. Cook, M. Youngblood, E. O. Heierman III, K. Gopalratnam, S. Rao, A. Litvin*, et al.*, "MavHome: An agent-based smart home," in *2013 IEEE international conference on pervasive computing and communications (PerCom)*, 2003, pp. 521-521.
[22] I. Korhonen, R. Lappalainen, T. Tuomisto, T. Koobi, V. Pentikainen, M. Tuomisto*, et al.*, "TERVA: wellness monitoring system," in *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE*, 1998, pp. 1988-1991.
[23] T. Adlam, R. Faulkner, R. Orpwood, K. Jones, J. Macijauskiene, and A. Budraitiene, "The installation and support of internationally distributed equipment for people with dementia," *IEEE transactions on information technology in biomedicine: a publication of the IEEE Engineering in Medicine and Biology Society,* vol. 8, pp. 253-257, 2004.
[24] N. Barnes, N. Edwards, D. Rose, and P. Garner, "Lifestyle monitoring-technology for supported independence," *Computing & Control Engineering Journal,* vol. 9, pp. 169-174, 1998.
[25] T. Yamazaki, "Ubiquitous home: real-life testbed for home context-aware service," in *Testbeds and Research Infrastructures for the Development of Networks and Communities, 2005. Tridentcom 2005. First International Conference on*, 2005, pp. 54-59.
[26] J.-H. Do, H. Jang, S. H. Jung, J. Jung, and Z. Bien, "Soft remote control system in the intelligent sweet home," in *Intelligent Robots and Systems, 2005.(IROS 2005). 2005 IEEE/RSJ International Conference on*, 2005, pp. 3984-3989.
[27] A. Yamaguchi, M. Ogawa, T. Tamura, and T. Togawa, "Monitoring behavior in the home using positioning sensors," in *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE*, 1998, pp. 1977-1979.
[28] N. Zhu, T. Diethe, M. Camplani, L. Tao, A. Burrows, N. Twomey*, et al.*, "Bridging e-Health and the Internet of Things: The SPHERE Project," *Intelligent Systems, IEEE,* vol. 30, pp. 39-46, 2015.
[29] University of Alberta. (2015, 10/08/2005). *Smart Condo project*. Available: http://www.hserc.ualberta.ca/Resources/Spaces/SmartCondo.aspx
[30] M. Chan, E. Campo, and D. Estève, "Assessment of activity of elderly people using a home monitoring system," *International Journal of Rehabilitation Research,* vol. 28, pp. 69-76, 2005.
[31] A. Reiss and D. Stricker, "Introducing a new benchmarked dataset for activity monitoring," in *Wearable Computers (ISWC), 2012 16th International Symposium on*, 2012, pp. 108-109.
[32] "AMBIENT ASSISTED LIVING," 2011.

[33] B. Celler, W. Earnshaw, E. Ilsar, L. Betbeder-Matibet, M. Harris, R. Clark*, et al.*, "Remote monitoring of health status of the elderly at home. A multidisciplinary project on aging at the University of New South Wales," *International journal of bio-medical computing,* vol. 40, pp. 147-155, 1995.
[34] T. V. Duong, D. Q. Phung, H. H. Bui, and S. Venkatesh, "Human behavior recognition with generic exponential family duration modeling in the hidden semi-markov model," in *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*, 2006, pp. 202-207.
[35] S. S. Intille, "Designing a home of the future," *IEEE pervasive computing,* vol. 1, pp. 76-82, 2002.
[36] I. Korhonen, J. Parkka, and M. Van Gils, "Health monitoring in the home of the future," *Engineering in Medicine and Biology Magazine, IEEE,* vol. 22, pp. 66-73, 2003.
[37] G. Demiris, M. J. Rantz, M. A. Aud, K. D. Marek, H. W. Tyrer, M. Skubic*, et al.*, "Older adults' attitudes towards and perceptions of'smart home'technologies: a pilot study," *Informatics for Health and Social Care,* vol. 29, pp. 87-94, 2004.
[38] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *IEEE journal of biomedical and health informatics,* vol. 17, pp. 579-590, 2013.
[39] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. 37, pp. 1067-1080, 2007.
[40] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys & Tutorials,* vol. 11, pp. 13-32, 2009.
[41] P. Steggles and S. Gschwind, *The Ubisense smart space platform*: na, 2005.
[42] R. Mautz, "Indoor positioning technologies," Habilitationsschrift ETH Zürich, 2012, 2012.
[43] U. Grossmann, M. Schauch, and S. Hakobyan, "The accuracy of algorithms for WLAN indoor positioning and the standardization of signal reception for different mobile devices," *International Journal of Computing,* vol. 6, pp. 103-109, 2014.
[44] N. Cislo, "Undernutrition prevention for disabled and elderly people in smart home with bayesian networks and rfid sensors," in *Aging Friendly Technology for Health and Independence*, ed: Springer, 2010, pp. 246-249.
[45] G. Postolache, P. S. Girão, C. M. Moura, and O. Postolache, "Rehabilitative TeleHealthCare for post-stroke outcome assessment," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2011 5th International Conference on*, 2011, pp. 408-413.
[46] H. Gu and D. Wang, "A content-aware fridge based on RFID in smart home for home-healthcare," in *Advanced Communication Technology, 2009. ICACT 2009. 11th International Conference on*, 2009, pp. 987-990.
[47] D. Zhang, J. Zhou, M. Guo, J. Cao, and T. Li, "TASA: Tag-free activity sensing using RFID tag arrays," *IEEE Transactions on Parallel and Distributed Systems,* vol. 22, pp. 558-570, 2011.
[48] M. Bouet and A. L. Dos Santos, "RFID tags: Positioning principles and localization techniques," in *1st IFIP Wireless Days (WD)*, 2008, pp. 1-5.
[49] K. Bouchard, J.-S. Bilodeau, D. Fortin-Simard, S. Gaboury, B. Bouchard, and A. Bouzouane, "Human activity recognition in smart homes based on passive RFID localization," in *Proceedings of the 7th International Conference on PErvasive Technologies Related to Assistive Environments*, 2014, p. 1.
[50] U. Varshney, "Patient monitoring using infrastructure-oriented wireless LANs," *International Journal of Electronic Healthcare,* vol. 2, pp. 149-163, 2006.
[51] M. Ciurana, S. Cugno, and F. Barceló-Arroyo, "WLAN indoor positioning based on TOA with two reference points," in *Positioning, Navigation and Communication, 2007. WPNC'07. 4th Workshop on*, 2007, pp. 23-28.

[52] C. Wong, R. Klukas, and G. Messier, "Using WLAN infrastructure for angle-of-arrival indoor user location," in *Vehicular Technology Conference, 2008. VTC 2008-Fall. IEEE 68th*, 2008, pp. 1-5.

[53] R. Tesoriero, J. Gallud, M. D. Lozano, and V. M. Penichet, "Tracking autonomous entities using RFID technology," *IEEE Transactions on Consumer Electronics,* vol. 55, pp. 650-655, 2009.

[54] Z. Farid, R. Nordin, and M. Ismail, "Recent advances in wireless indoor localization techniques and system," *Journal of Computer Networks and Communications,* vol. 2013, 2013.

[55] C. Hekimian-Williams, B. Grant, X. Liu, Z. Zhang, and P. Kumar, "Accurate localization of RFID tags using phase difference," in *IEEE International Conference on RFID*, 2010, pp. 89-96.

[56] J. Shang, S. Yu, and L. Zhu, "Location-aware systems for short-range wireless networks," in *Computer Network and Multimedia Technology, 2009. CNMT 2009. International Symposium on*, 2009, pp. 1-5.

[57] Y.-T. Chen, C.-L. Yang, Y.-K. Chang, and C.-P. Chu, "A RSSI-based algorithm for indoor localization using ZigBee in wireless sensor network," *Proc. of the 15th International Conference on Distributed Multimedia Systems (DMS 2009),* pp. 70-75, 2009.

[58] B.-S. Choi and J.-J. Lee, "Mobile robot localization in indoor environment using RFID and sonar fusion system," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, 2009, pp. 2039-2044.

[59] A. P. Sample, C. Macomber, L.-T. Jiang, and J. R. Smith, "Optical localization of passive UHF RFID tags with integrated LEDs," in *RFID (RFID), 2012 IEEE International Conference on*, 2012, pp. 116-123.

[60] M. Hasani, J. Talvitie, L. Sydänheimo, E.-S. Lohan, and L. Ukkonen, "Hybrid WLAN-RFID indoor localization solution utilizing textile tag," *IEEE Antennas and Wireless Propagation Letters,* vol. 14, pp. 1358-1361, 2015.

[61] H. Lee and J. Kwon, "The Smart Home Service System Architecture for Healthy and Safe Human Life," 2013.

[62] A. Helal, D. J. Cook, and M. Schmalz, "Smart home-based health platform for behavioral monitoring and alteration of diabetes patients," *Journal of diabetes science and technology,* vol. 3, pp. 141-148, 2009.

[63] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, "LANDMARC: indoor location sensing using active RFID," *Wireless networks,* vol. 10, pp. 701-710, 2004.

[64] K. Chawla and G. Robins, "An RFID-based object localisation framework," *International journal of radio frequency identification technology and applications,* vol. 3, pp. 2-30, 2011.

[65] A. Athalye, V. Savic, M. Bolic, and P. M. Djuric, "Novel semi-passive RFID system for indoor localization," *Sensors Journal, IEEE,* vol. 13, pp. 528-537, 2013.

[66] K. Bouchard, D. Fortin-Simard, S. Gaboury, B. Bouchard, and A. Bouzouane, "Accurate trilateration for passive RFID localization in smart homes," *International Journal of Wireless Information Networks,* vol. 21, pp. 32-47, 2014.

[67] M. Bolic, M. Rostamian, and P. M. Djuric, "Proximity Detection with RFID: A Step Toward the Internet of Things," *IEEE Pervasive Computing,* pp. 70-76, 2015.

[68] Y. Zhao, Y. Liu, and L. M. Ni, "VIRE: Active RFID-based localization using virtual reference elimination," in *International Conference on Parallel Processing. ICPP 2007*, 2007, pp. 56-56.

[69] K.-L. Sue, C.-H. Tsai, and M.-H. Lin, "FLEXOR: A flexible localization scheme based on RFID," in *Information Networking Advances in Data Communications and Wireless Networks*, ed: Springer, 2006, pp. 306-316.

[70] T. Zhang, Z. Chen, Y. Ouyang, J. Hao, and Z. Xiong, "An improved RFID-based locating algorithm by eliminating diversity of active tags for indoor environment," *The Computer Journal,* vol. 52, pp. 902-909, 2009.

[71] D. Hahnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose, "Mapping and localization with RFID technology," in *Proceedings IEEE International Conference on Robotics and Automation. ICRA'04.* , 2004, pp. 1015-1020.
[72] D. Fortin-Simard, K. Bouchard, S. Gaboury, B. Bouchard, and A. Bouzouane, "Accurate passive RFID localization system for smart homes," in *Proceedings - 2012 IEEE 3rd International Conference on Networked Embedded Systems for Every Application, NESEA* 2012.
[73] P. Vorst, S. Schneegans, B. Yang, and A. Zell, "Self-localization with RFID snapshots in densely tagged environments," in *IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS 2008.* , 2008, pp. 1353-1358.
[74] D. Joho, C. Plagemann, and W. Burgard, "Modeling RFID signal strength and tag detection for localization and mapping," in *IEEE International Conference on Robotics and Automation. ICRA'09*, 2009, pp. 3160-3165.
[75] R. D'Errico, M. Bottazzi, F. Natali, E. Savioli, S. Bartoletti, A. Conti*, et al.*, "An UWB-UHF semi-passive RFID System for localization and tracking applications," in *IEEE International Conference on RFID-Technologies and Applications, RFID-TA* 2012, pp. 18-23.
[76] Z. Xiong, Z. Song, A. Scalera, E. Ferrera, F. Sottile, P. Brizzi*, et al.*, "Hybrid WSN and RFID indoor positioning and tracking system RFID and near field communications in embedded systems," *Eurasip Journal on Embedded Systems,* vol. 2013, 2013.
[77] S. Park and S. Hashimoto, "An intelligent localization algorithm using read time of RFID system," *Advanced Engineering Informatics,* vol. 24, pp. 490-497, 2010.
[78] B. Jachimczyk, D. Dziak, and W. J. Kulesza, "RFID-Hybrid Scene Analysis-Neural Network System for 3D Indoor Positioning optimal system arrangement approach," in *Proceedings IEEE International Instrumentation and Measurement Technology Conference (I2MTC)* 2014, pp. 191-196.
[79] P. Yang, W. Wu, M. Moniri, and C. C. Chibelushi, "Efficient object localization using sparsely distributed passive RFID tags," *IEEE Transactions on Industrial Electronics,* vol. 60, pp. 5914-5924, 2013.
[80] W. Ruan, L. Yao, Q. Z. Sheng, N. J. Falkner, and X. Li, "TagTrack: device-free localization and tracking using passive RFID tags," in *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, 2014, pp. 80-89.
[81] J. Han, C. Qian, X. Wang, D. Ma, J. Zhao, P. Zhang*, et al.*, "Twins: Device-free object tracking using passive tags," in *Proceedings IEEE INFOCOM* 2014, pp. 469-476.
[82] B. Wagner and D. Timmermann, "Adaptive clustering for device free user positioning utilizing passive RFID," in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, 2013, pp. 499-508.
[83] J. Shen, A. F. Molisch, and J. Salmi, "Accurate passive location estimation using TOA measurements," *IEEE Transactions on Wireless Communications,* vol. 11, pp. 2182-2192, 2012.
[84] D. Kim, J. Ha, P. Kim, and K. You, "TDOA/AOA localization in RFID system using dual indirect Kalman filter," in *IEEE/SICE International Symposium on System Integration (SII)*, 2011, pp. 440-445.
[85] A. Povalac and J. Sebesta, "Phase difference of arrival distance estimation for RFID tags in frequency domain," in *RFID-Technologies and Applications (RFID-TA), 2011 IEEE International Conference on*, 2011, pp. 188-193.
[86] K. Chawla, C. McFarland, G. Robins, and C. Shope, "Real-time RFID localization using RSS," in *International Conference on Localization and GNSS (ICL-GNSS)*, 2013, pp. 1-6.
[87] S. Azzouzi, M. Cremer, U. Dettmar, T. Knie, and R. Kronberger, "Improved AoA based localization of UHF RFID tags using spatial diversity," in *IEEE International Conference on RFID-Technologies and Applications (RFID-TA)*, 2011, pp. 174-180.

[88] J. Song, C. T. Haas, and C. H. Caldas, "A proximity-based method for locating RFID tagged objects," *Advanced Engineering Informatics,* vol. 21, pp. 367-376, 2007.
[89] D.-S. Seo, D. Won, G.-W. Yang, M.-S. Choi, S.-J. Kwon, and J. W. Park, "A probabilistic approach for mobile robot localization under RFID tag infrastructures," *International Conference on Control, Automation, and Systems (ICCAS 2005),* pp. 1797-1801, 2005.
[90] M. Moreno-Cano, M. A. Zamora-Izquierdo, J. Santa, and A. F. Skarmeta, "An indoor localization system based on artificial neural networks and particle filters applied to intelligent buildings," *Neurocomputing,* vol. 122, pp. 116-125, 2013.
[91] K. Yamano, K. Tanaka, M. Hirayama, E. Kondo, Y. Kimuro, and M. Matsumoto, "Self-localization of mobile robots with RFID system by using support vector machine," in *Proceedings IEEE/RSJ International Conference on Intelligent Robots and Systems. (IROS 2004)* 2004, pp. 3756-3761.
[92] C. C. Tan, B. Sheng, and Q. Li, "How to monitor for missing RFID tags," in *The 28th International Conference on Distributed Computing Systems. ICDCS'08.* , 2008, pp. 295-302.
[93] D.-Y. Kim, H.-G. Yoon, B.-J. Jang, and J.-G. Yook, "Interference analysis of UHF RFID systems," *Progress In Electromagnetics Research B,* vol. 4, pp. 115-126, 2008.
[94] U. DeSA, "World population prospects: The 2012 revision," *Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, New York,* 2013.
[95] L. Yang, J. Han, Y. Qi, C. Wang, T. Gu, and Y. Liu, "Season: Shelving interference and joint identification in large-scale RFID systems," in *Proceedings IEEE INFOCOM*, 2011, pp. 3092-3100.
[96] medicinenet. (2012). *Definition of ADLs (activities of daily living)*. Available: http://www.medicinenet.com/script/main/art.asp?articlekey=2152
[97] A. S. Crandall, "Behaviometrics for multiple residents in a Smart homes," 2011.
[98] S. Wang and G. Zhou, "A review on radio based activity recognition," *Digital Communications and Networks,* vol. 1, pp. 20-29, 2015.
[99] S. Abbate, M. Avvenuti, and J. Light, "Usability study of a wireless monitoring system among Alzheimer's disease elderly population," *International journal of telemedicine and applications,* vol. 2014, p. 7, 2014.
[100] A. M. Khan, "Human activity recognition using a single tri-axial accelerometer," Kyung Hee University Seoul, Korea, 2011.
[101] S.-R. Ke, H. L. U. Thuc, Y.-J. Lee, J.-N. Hwang, J.-H. Yoo, and K.-H. Choi, "A review on video-based human activity recognition," *Computers,* vol. 2, pp. 88-131, 2013.
[102] J. Lei, X. Ren, and D. Fox, "Fine-grained kitchen activity recognition using rgb-d," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, 2012, pp. 208-211.
[103] J. Shotton, T. Sharp, A. Kipman, A. Fitzgibbon, M. Finocchio, A. Blake*, et al.*, "Real-time human pose recognition in parts from single depth images," *Communications of the ACM,* vol. 56, pp. 116-124, 2013.
[104] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Systems with Applications,* vol. 40, pp. 1662-1674, 2013.
[105] J. Wu, A. Osuntogun, T. Choudhury, M. Philipose, and J. M. Rehg, "A scalable approach to activity recognition based on object use," in *Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on*, 2007, pp. 1-8.
[106] K. Wongpatikaseree, M. Ikeda, M. Buranarach, T. Supnithi, A. O. Lim, and Y. Tan, "Activity recognition using context-aware infrastructure ontology in smart home domain," in *Knowledge, Information and Creativity Support Systems (KICSS), 2012 Seventh International Conference on*, 2012, pp. 50-57.

[107] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive and Mobile Computing,* vol. 10, Part B, pp. 138-154, 2// 2014.

[108] Q. Ni, A. B. García Hernando, and I. P. de la Cruz, "The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development," *Sensors,* vol. 15, pp. 11312-11362, 2015.

[109] R. Khusainov, D. Azzi, I. E. Achumba, and S. D. Bersch, "Real-time human ambulation, activity, and physiological monitoring: taxonomy of issues, techniques, applications, challenges and limitations," *Sensors,* vol. 13, pp. 12852-12902, 2013.

[110] I. technologies. *Monitoring Readers and Gateways using SNMP*. Available: https://support.impinj.com/hc/en-us/articles/212639907-Monitoring-Readers-and-Gateways-using-SNMP

[111] Impinj. *Low Level User Data Support*. Available: https://support.impinj.com/hc/en-us/articles/202755318-Application-Note-Low-Level-User-Data-Support

[112] J. A. Shaw, "Radiometry and the Friis transmission equation," *American Journal of Physics,* vol. 81, pp. 33-37, 2013.

[113] J. S. Choi, H. Lee, R. Elmasri, and D. W. Engels, "Localization systems using passive UHF RFID," in *INC, IMS and IDC, 2009. NCM'09. Fifth International Joint Conference on*, 2009, pp. 1727-1732.

[114] P. V. Nikitin and K. Rao, "Antennas and propagation in UHF RFID systems," *challenge,* vol. 22, p. 23, 2008.

[115] T. H. Dao, Q. C. Nguyen, M. T. Le, and C. A. Hoang, "Indoor Localization System Based on Passive RFID Tags," in *Intelligent Systems, Modelling and Simulation (ISMS), 2014 5th International Conference on*, 2014, pp. 579-584.

[116] Y.-P. Luh and Y.-C. Liu, "Measurement of effective reading distance of UHF RFID passive tags," 2013.

[117] O. Desjeux and E. Rusca, "Method to Determine a Field Strength by a Reader for Telemetry Units," ed: Google Patents, 2010.

[118] B. Cook, G. Buckberry, I. Scowcroft, J. Mitchell, and T. Allen, "Indoor location using trilateration characteristics," *Proc. London Communications Symposium,* pp. 147-150, 2005.

[119] K. Chawla, "An RFID-Based Object Localization Framework and System," University of Virginia, 2014.

[120] D. Zhang, F. Xia, Z. Yang, L. Yao, and W. Zhao, "Localization technologies for indoor human tracking," in *2010 5th International Conference on Future Information Technology*, 2010, pp. 1-6.

[121] H. Karl and A. Willig, *Protocols and architectures for wireless sensor networks*: John Wiley & Sons, 2007.

[122] B. Alsinglawi, T. Liu, Q. Nguyen, U. Gunawardana, A. Maeder, and S. Simoff, "Passive RFID Localisation Framework in Smart Homes Healthcare Settings," *Studies in health technology and informatics,* vol. 231, p. 1, 2016.

A. APPENDIX A

In this Appendix we present a detailed overview of experimental results, evaluation, and a comparison of RFID based systems from literature review.

6.1 RFID Smart Homes Projects

Table 11. Comparison based solutions for Smart Homes using RFID

Solution	Application	Accuracy / Efficiency	Technique / Tracking	Hardware* / Coverage **	Benefits / Drawbacks
LANDMARC [63], 2004[E]	Location awareness	≤ 2m	References tags	9/ 64	Cost effective solution. • Less infrastructure required during deployment Minimises the localisation error caused by environmental interference (more precise)
		1m (50%) 5.9m (90%)	Active tags	N/A	Complexity and flexibility such as: Long latency. Different tag behaviour during detection (different reading values)
Jin et al.,2006[3][E]	Location awareness	72cm	Reference tags	4/20	The new mechanism (based on previous work by LANDMARK) to reduce the computational load caused by tags (reduced number of neighbour tags).
		83cm (per 10 tags in 2m "average tolerance ")	Active tags	N/A	System used changes active tags (high cost and battery requirement) Complexity and maintenance issues.

FLEXER,2006 [69][S]	Location awareness (indoor localisation)	40cm-1m	Reference tags	4/64	Flexible localisation method (localise region mode and coordinates) Reduces computational load and enhances the localisation speed
		70cm (80%) Region mode	Active tags	49^2	System used Active tags (high cost, battery requirement) System complexity implementation
VIRE[68], 2007[E]	Indoor localisation	1.5m	Reference tags	4/16	Cost effective solution
		0.5m	Active tags	N/A	Lack of the solution in large scale Complexity and maintenance issues (battery requirement)
Zhang et al, [70][S] 2009	Location awareness	10cm (1m space between tags	Reference tags	4/49	Reducing the diversities of tags in a home environment and the mean locating error.
		19cm (2.4m space between tags)	Active tags	100m	High cost and system rely on active tag battery requirement). High complexity and needs maintenance.
Hekimian-Williams et al[55][T],2010	Location awareness	Millimetres accuracy	Phase Difference	2/1	Very precise and highly accurate approach (accuracy in millimetres)
		Very precise	Active tags	18m	Not applicable for tag localisation for Passive tags. High cost (active tags are expensive and need *a* battery) High complexity and that needs maintenance. The system suffers from intrusiveness that resulted from multipath.
Hahnel et al[71][T], 2004	Indoor positioning	$\leq$ 2m	References tags	2/100	Map learning approach using Mobile Robot

	(robot localisation)	1m-1.4m	Passive tags	28^2	Required several RFID tags (high cost and high complexity) Line of sight issues (Laser range scan)
Vorst et al [73], 2008	Indoor localisation (mobile robot)	20cm-26cm	Reference tags	4/374	Proposed probabilistic fingerprint technique (in particle filter) for considerable accuracy.
		≈ 0.25cm 0.32cm(90%)	Passive Tags	125m	High cost with many tags and readers High complexity due to the large number of tags and readers
Joho et al [74], 2009	Indoor localisation (mapping)	27cm-29cm	References tags	1/350	Probabilistic sensor model (Sensor calibration) based on RSSI to improve *the* accuracy of the system
		≈ 35cm	Passive Tags	N/A	High cost as adding more tags will add extra costs to the system
Tesoriero et al [53], 2009	Indoor Tracking (autonomous entities)	≈ 0.9 m	Sense Analysis	1/19	Locating objects based on entities (inside grids) Virtual mapping
		Error = 0 (50% speed against 19 tags Error = 10% (75% / 18tags) Error = 20% (100% / 14 tags)	Passive tags	43^2	High cost as it requires many tags for more efficient and accurate localisation. Usability issues. High complexity, every object (even smaller, cups, kettle, etc.) need to be attached to readers for localisation.
Sunhong et al [77], 2010	Indoor Tracking (robot location)	≈ 10cm	References tags	1/198	A method to reduce the number of used tags and sensors.

		N/A	Passive tags	26m	Usability issues, limited localisation application (not suitable for real time for non-disabled elderly individuals)
Chawla et al[64],2011	Indoor localisation (object localisation)	0.18cm	References tags	1/132	Several algorithms to achieve higher accuracy and efficient solution
		0.35cm (overall average)	Passive tags	8m	Need to deploy *a* large number of tags for higher accuracy High complexity and installation issues
D'Errico, R., et al. (2012)[75][S&E]	Indoor localisation (Real time tracking)	20cm	TOA	4/Many	Minimise energy consumption (battery) by enabling semi-active tags with UWB antenna and improved synchronisation.
		0.37m-0.53m (75%)	Hybrid (UWB-Semi-active tags)	N/A	High cost (adding more tags and readers will increase *the cost of the* whole system) Line-of-sight and multipath problems Interferences High complexity and maintenance issues Usability issues
Fortin-Simard, D., et al. (2012)[72]	Indoor localisation (Real-time tracking)	≈ 14cm	Trilateration/RSSI	4/4	New trilateration positioning model with various existing filters and fuzzy logic to achieve accuracy and system efficiency.
		≈ 32.5cm (higher efficiency)	Passive Tags	$6m^2$	Results obtained in limited coverage area (no actual test for various objects in Smart Homes e.g. furniture, different sized and shapes) Limited to positioning simple objects and does not cover multiple objects.
Yang, Wu et al. 2013[79]	Location awareness	10cm	References tags	4/96	High accuracy based on tag distribution (grid approach)
		10cm± 2.56 cm	Passive tags	N/A	The results are varied upon different localisation algorithms and RFID tags.

Athalye, Savic et al. 2013[65]	Location awareness	30cm	References tags	1/12	New Sense tags which have a dual ability to locate objects
		≤ 40cm CDF Method	Semi-Active	$6m^2$	Battery life issues caused by a comparator that runs whole power circuit.
Xiong, Song et al. 2013 [76][E&S]	Indoor Tracking (people / objects)	1.6m	RSSI	4/N/A	Cost effective approach (combined WSN with RFID devices) Robust IPS solution (effective solution in harsh environment)
		1.8m (hcEKF algorithm)	Hybrid RFID Passive Tags/WSN	300^2	The system was not tested in *a* large-scale experimental space.
Bouchard, Fortin-Simard et al. 2014[66]	Indoor tracking (people) / Activities of Daily Living (ADL) detection	≈ 16cm	Trilateration/RSSI	8/4	*Reduced* inaccuracy by applying some localisation filters New mapping protocols
		Correct (67.2%) 16cm	Passive Tags	$9m^2$	The system was not tested *on a* large scale with different zones. Lack of real-time tracking for multiple objects.
Jachimczyk et al [78], 2014 [S&E]	Indoor positioning (3D localisation)	7cm,11cm(based on 4 and 8 respectively readers)	TOA/RSS	8/N/A	More robustness and avoided obstacles Various configuration of active RFID Readers

		49cm, 50cm (based on 4 and 8 readers)	3D passive tags- Hybrid	46.17[3]	Higher cost depends on how many RFID readers used *in* the configuration. High system complexity and more computational cost based on the scenarios
Bolic et al [67][E]	Indoor localisation (proximity detection)	32 cm	Proximity	2 /N/A	Inexpensive UHF RFID tags and they are maintenance free
		48 cm	Passive tags	4m*2m	Requirement of landmark tags for localisation application Relying on semi-passive tags (needs battery changes)
Alsinglawi et al [122] [E]	Location estimation in Healthcare settings	16.5 cm	Trilateration/RSSI	3/1 1.1m*1.2m	Good accuracy levels with minimum tracking resources Cost-effective

Note: Experimental results (E); Simulation results (S); Simulation and Experimental Results (S&E); Target location for human tracking (H); and for tracking (T) only. *Hardware = Readers/ Tags / ** Coverage m/m2/m3

6.2 Tag Selection Procedure Experiments

6.2.1 Power level RSSI Selection procedure.

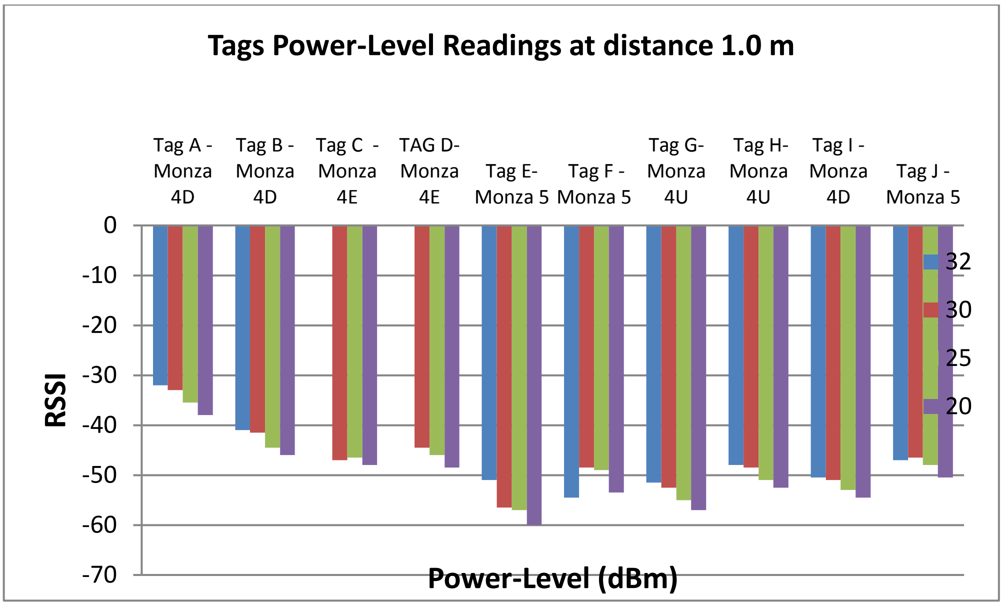

Figure A.1 Tags Power Level Readings at a Distance of 1.0 m

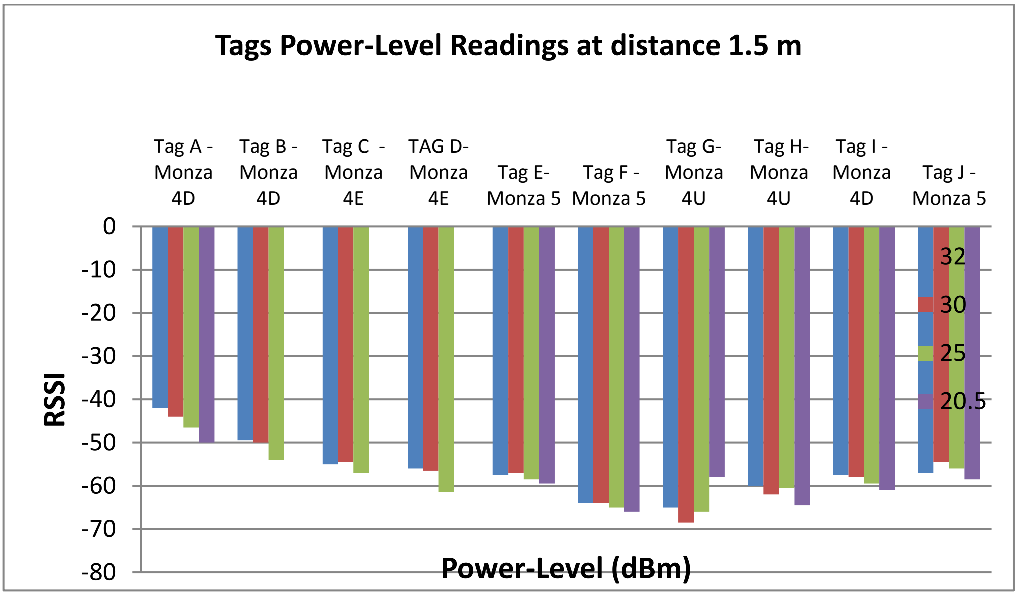

Figure A.2 Tags Power Level Readings at a Distance of 1.5 m

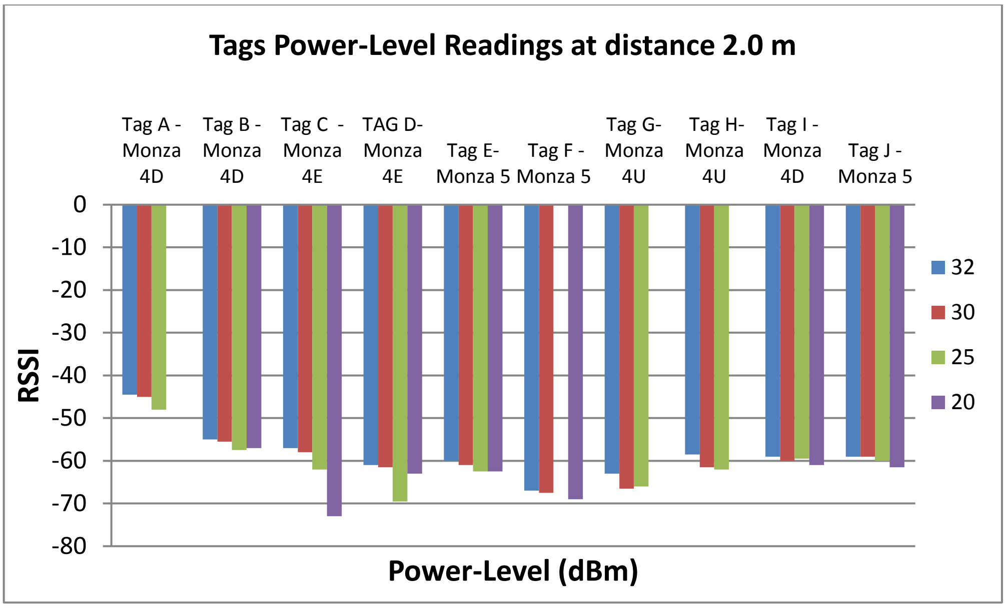

Figure A.3 Tags Power Level Readings at a Distance 2.0 m

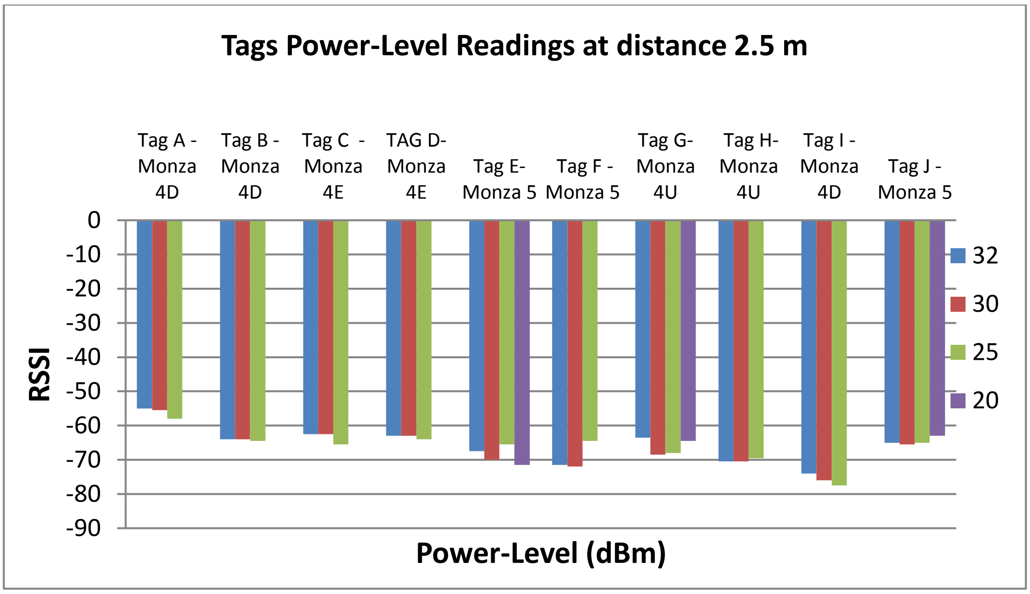

Figure A.4 Tags Power Level Readings at a Eistance of 2.5 m

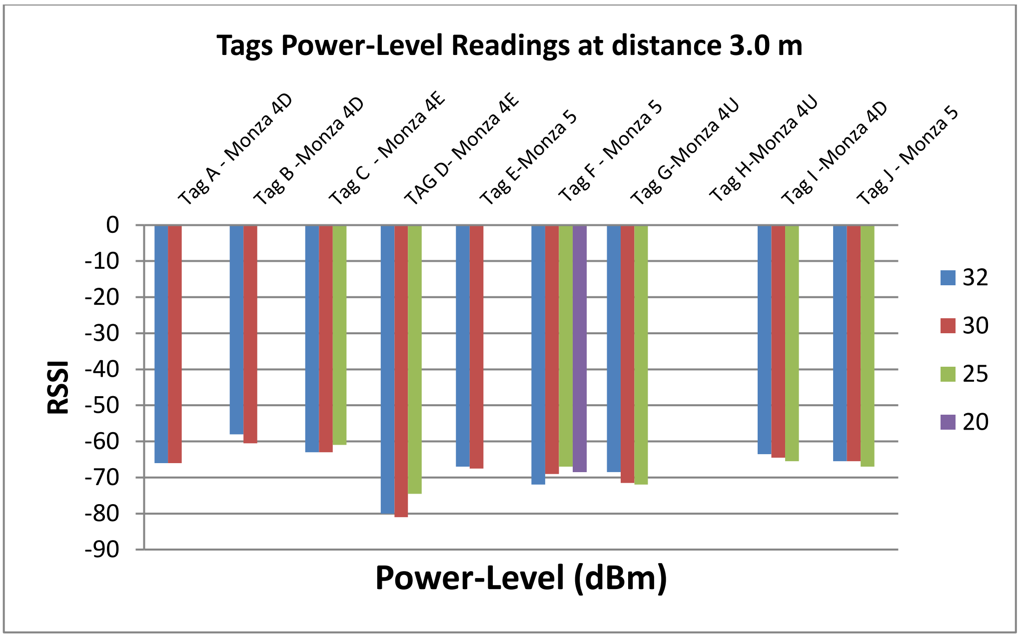

Figure A.5 Tags Power Level Readings at a Distance of 3.0 m

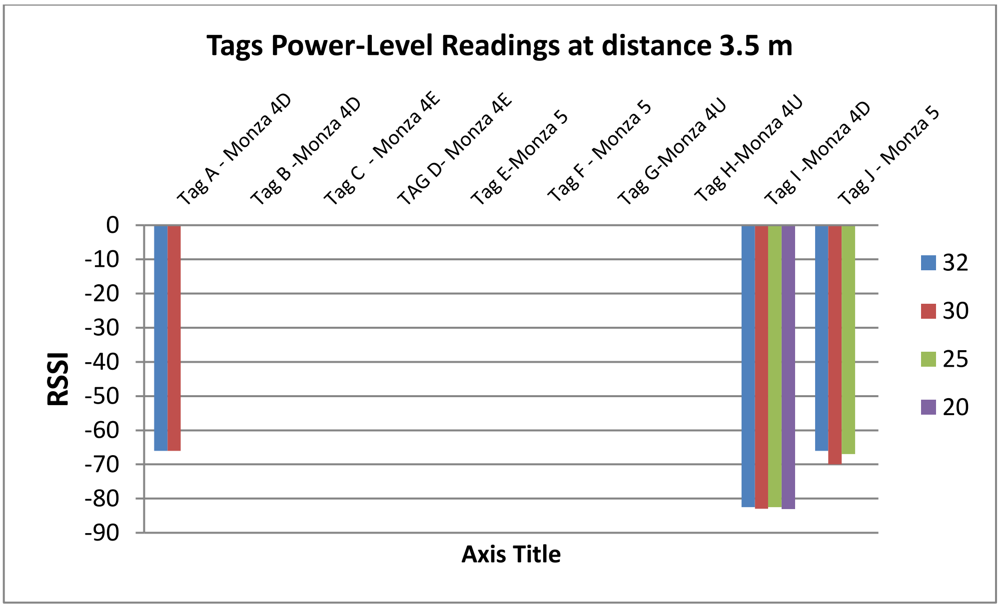

Figure A.6 Tags Power Level Readings at a Distance of 3.5 m

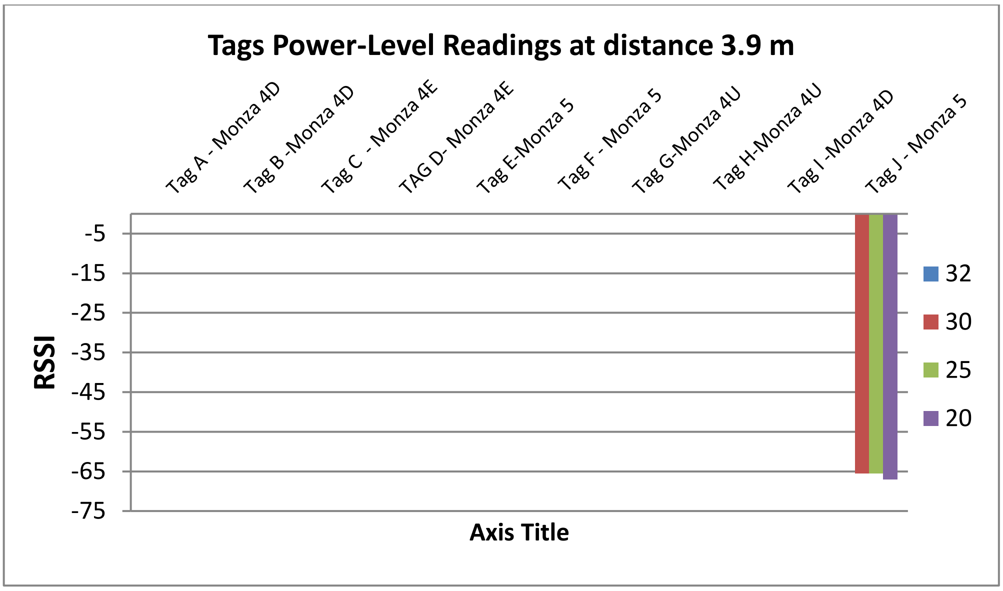

Figure A.7 Tags Power Level Readings at a Distance of 3.9 m

6.2.2 Tag Sensitivity Readings

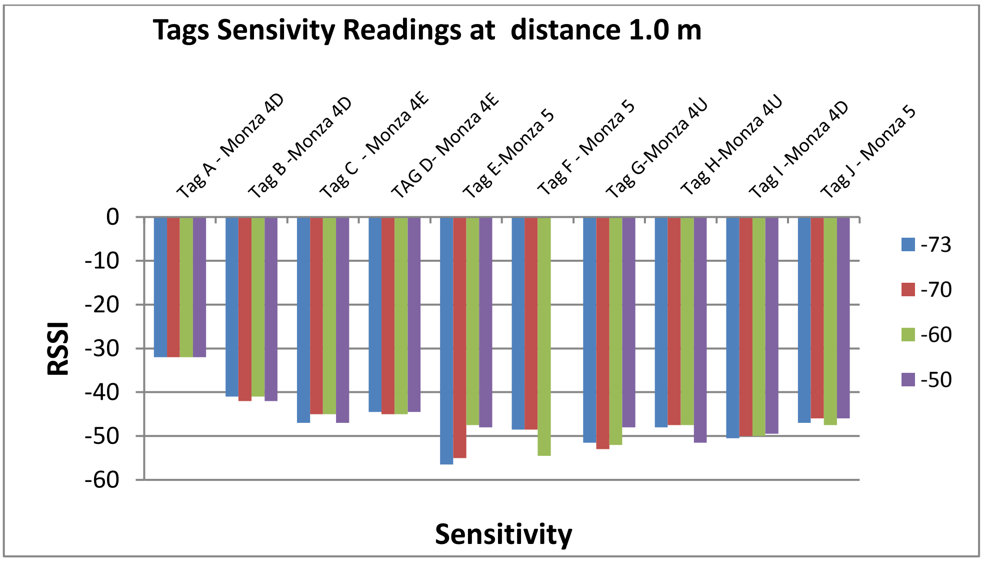

Figure A.8 Tag Sensitivity Readings at a Distance of 1.0 m

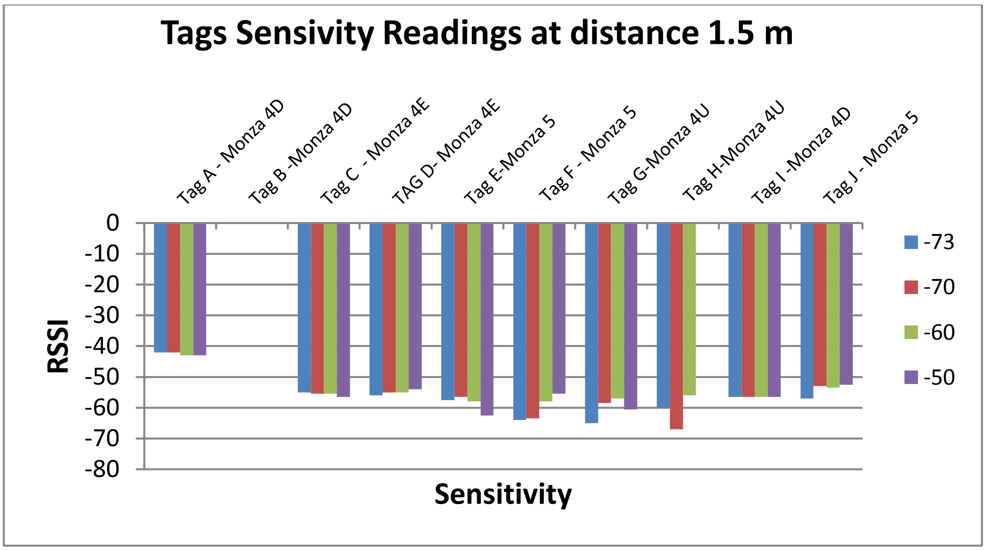

Figure A.9 Tag Sensitivity Readings at a Distance of 1.5 m

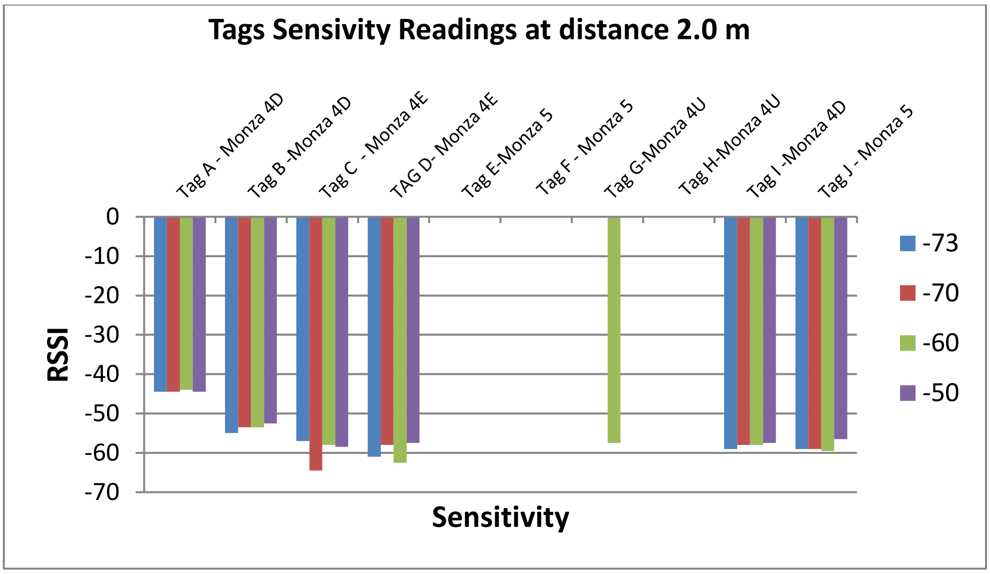

Figure A.10 Tags Sensitivity Readings at a Distance of 2.0 m

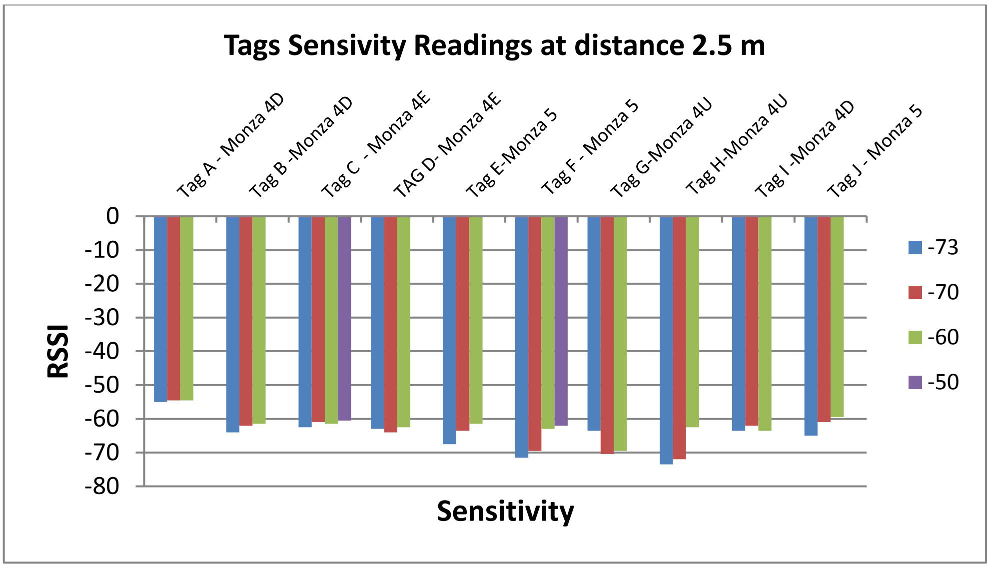

Figure A.11 Tags Sensitivity Readings at a Distance of 2.5 m

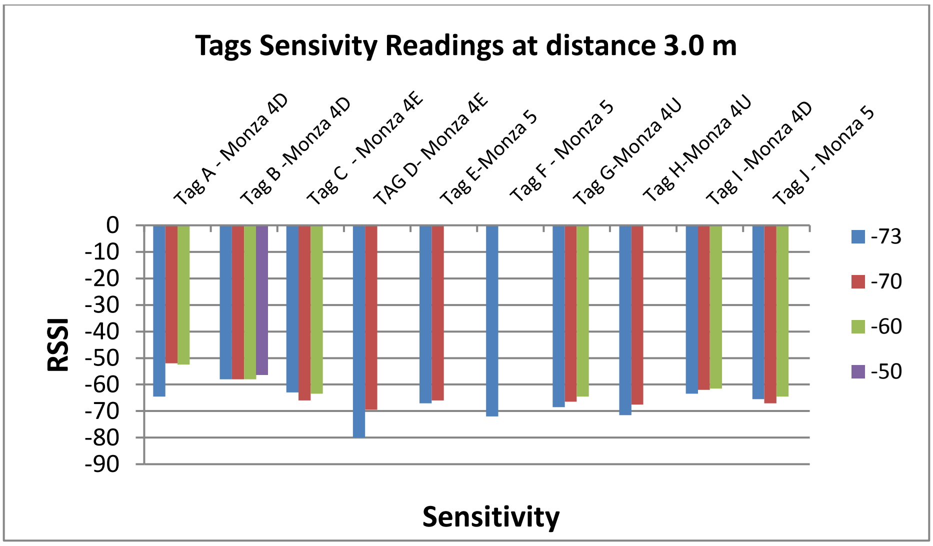

Figure A.12 Tags Sensitivity Readings at a Distance of 3.0 m

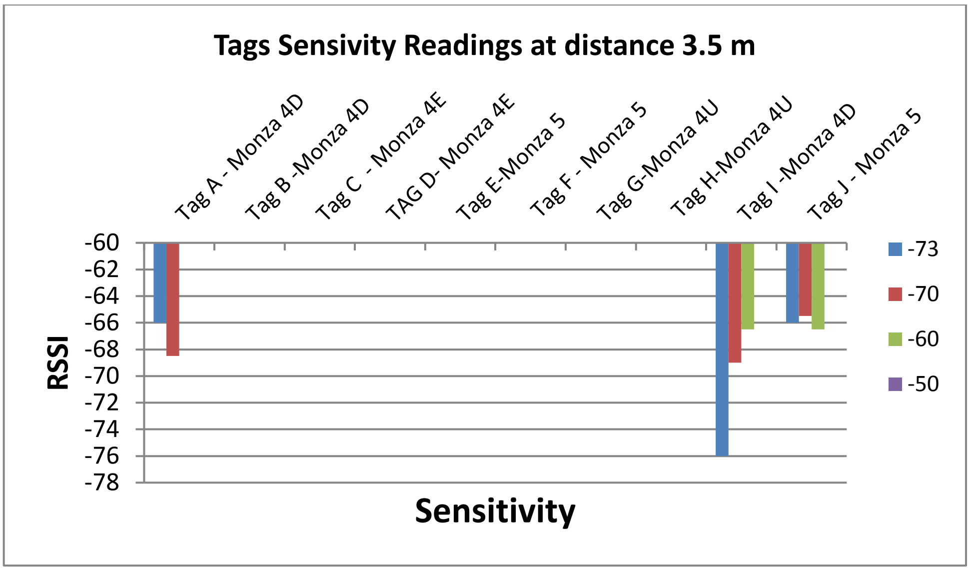

Figure A.13 Tags Sensitivity Readings at a Distance of 3.5 m

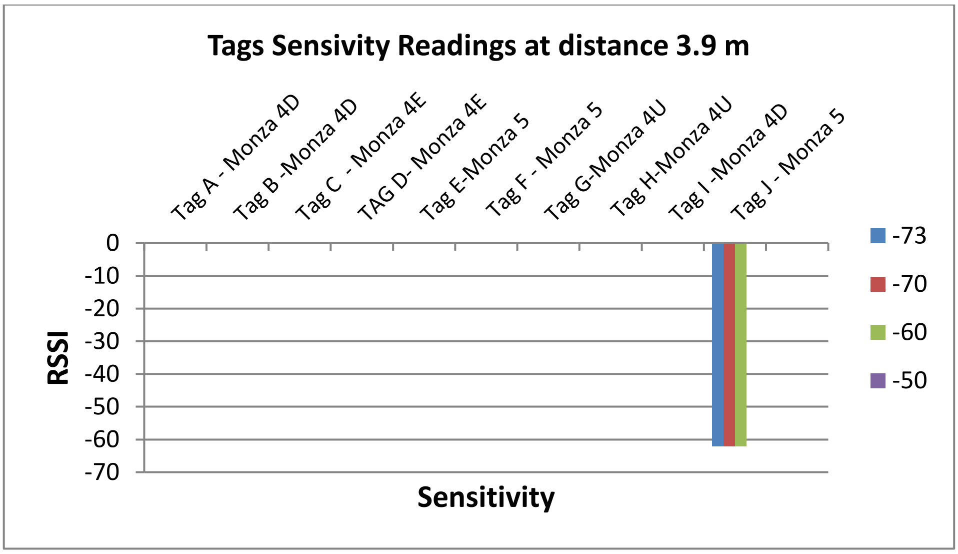

Figure A.14 Tags Sensitivity Readings at a Distance of 3.9 m

6.3 RFID Antennas height Calibration Experiments

Antenna 1 calibration experiments evaluation.

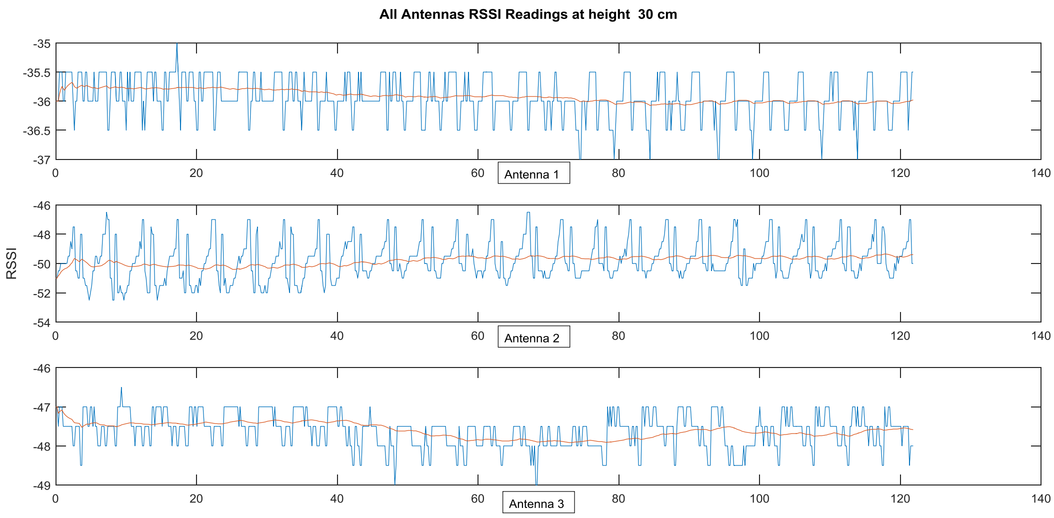

Figure A.15 Antenna's Readings at height 30 cm

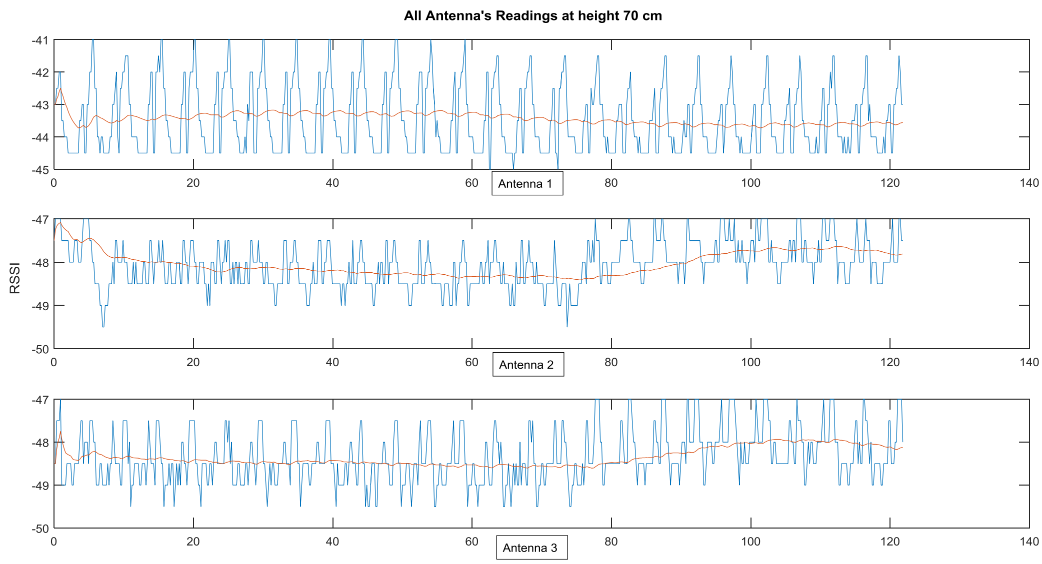

Figure A.16 Antenna's Readings at height 70 cm

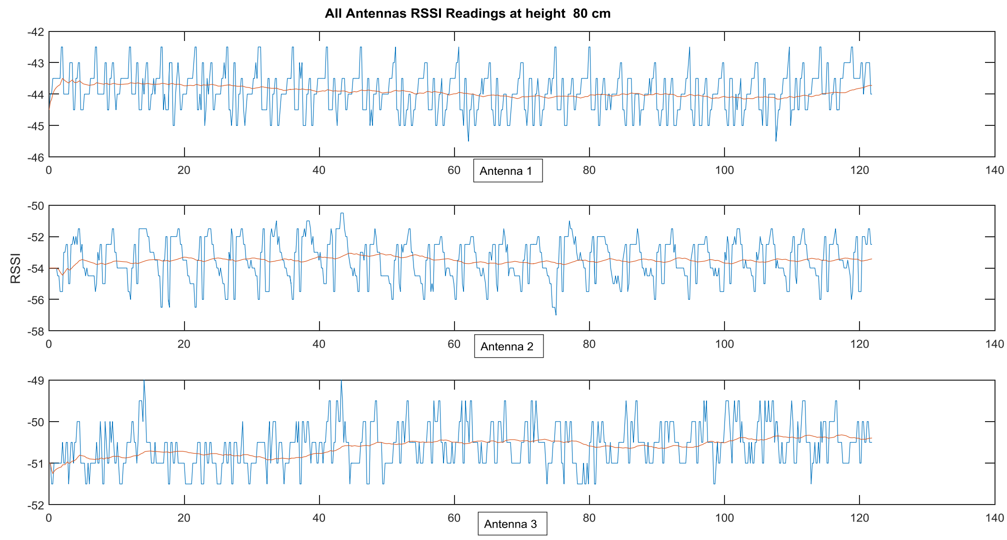

Figure A.17 Antenna's Readings at height 80 cm

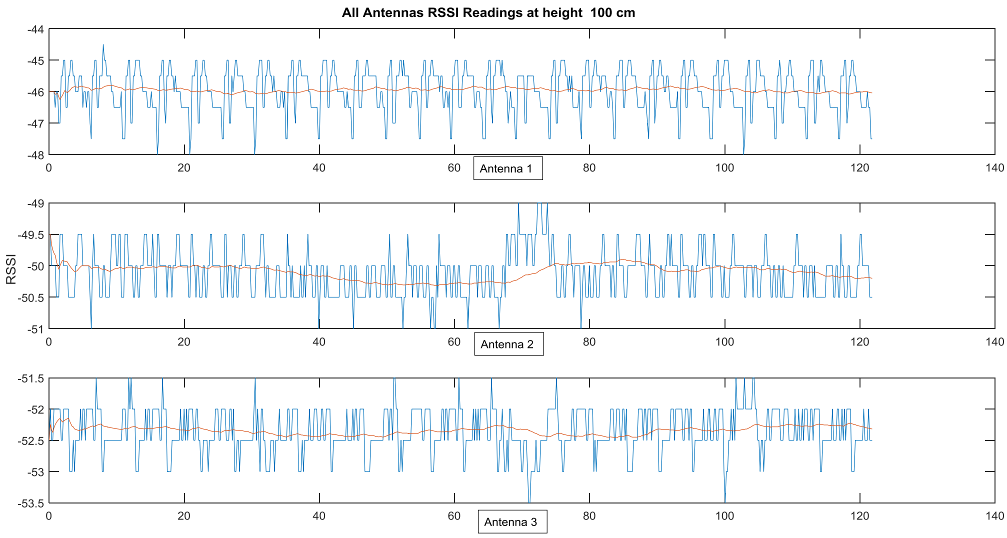

Figure A.18 Antenna's Readings at height 100 cm

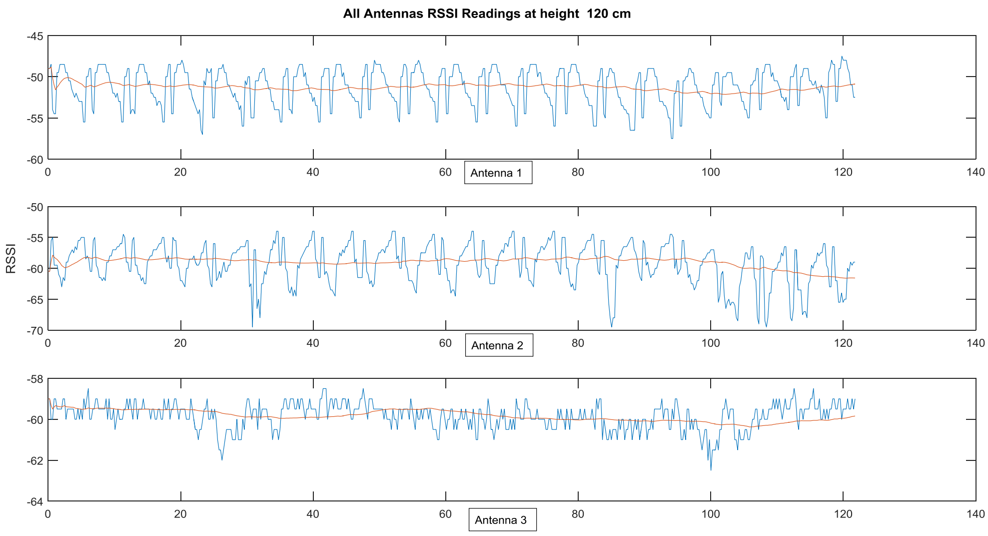

Figure A.19 Antenna's Readings at height 120 cm

6.4 Tag A orientation calibration at various distances from target antenna experiments

6.4.1 Tag A facing antennas 1 at various distances experiment

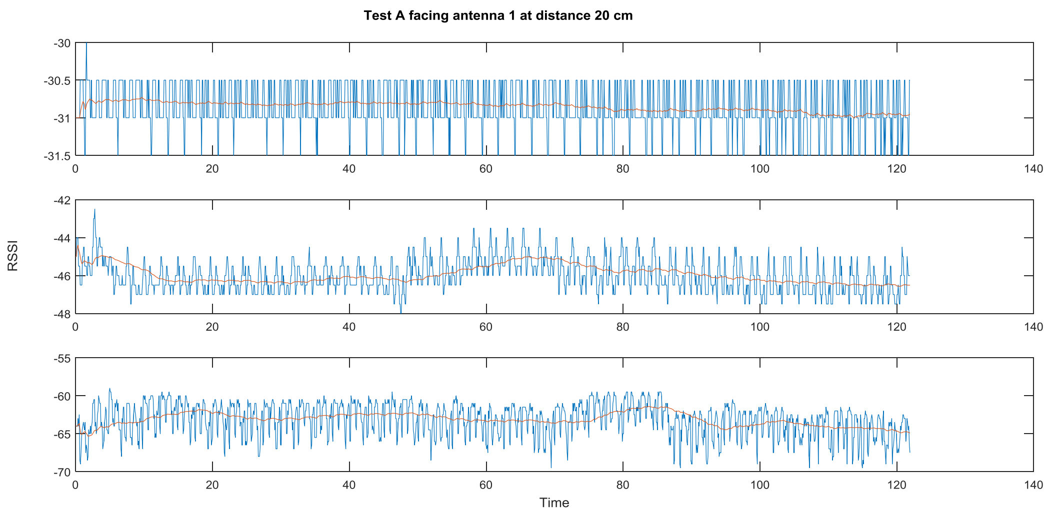

Figure A.20 tag A facing antenna 1 at distance 20 cm

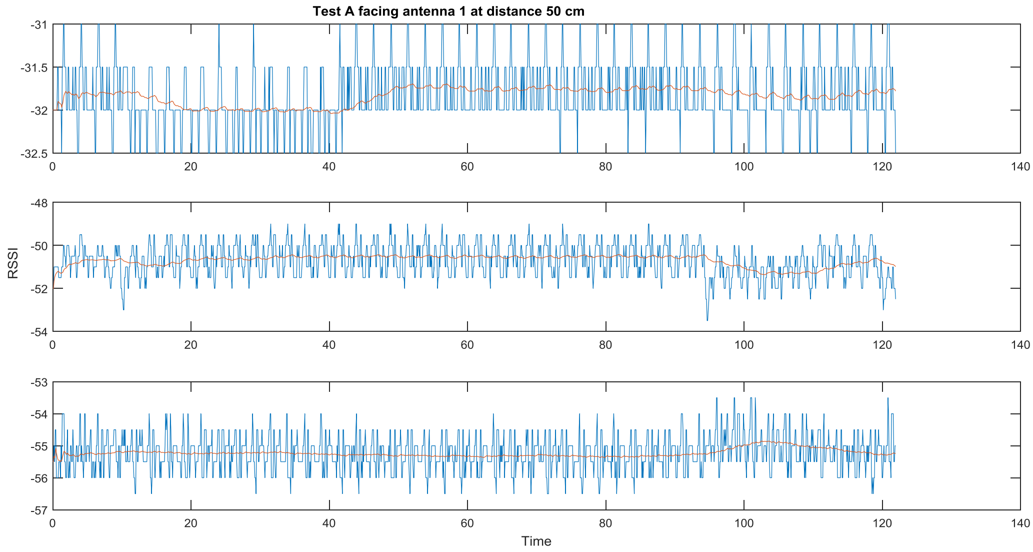

Figure A.21 tag A facing antenna 1 at distance 50 cm

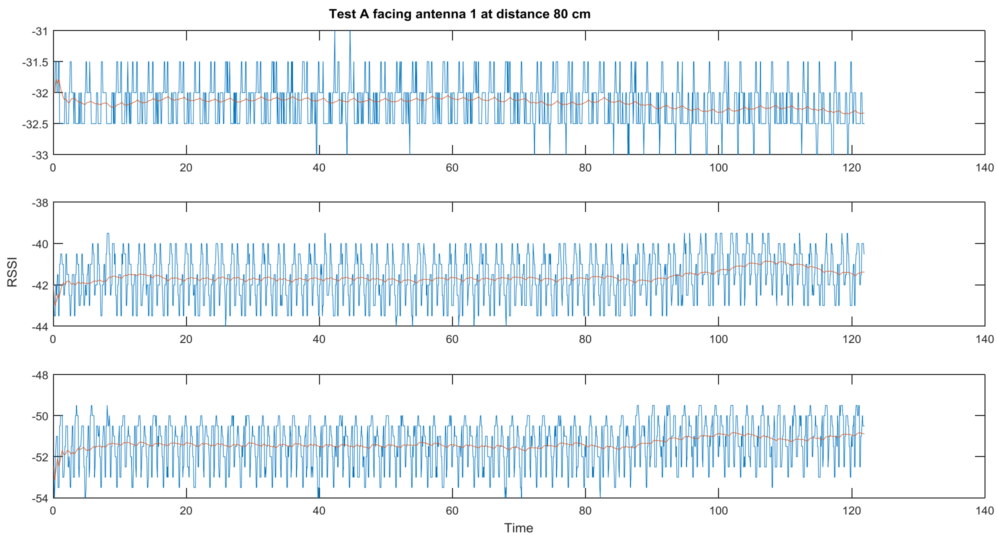

Figure A.22 tag A facing antenna 1 at distance 80 cm

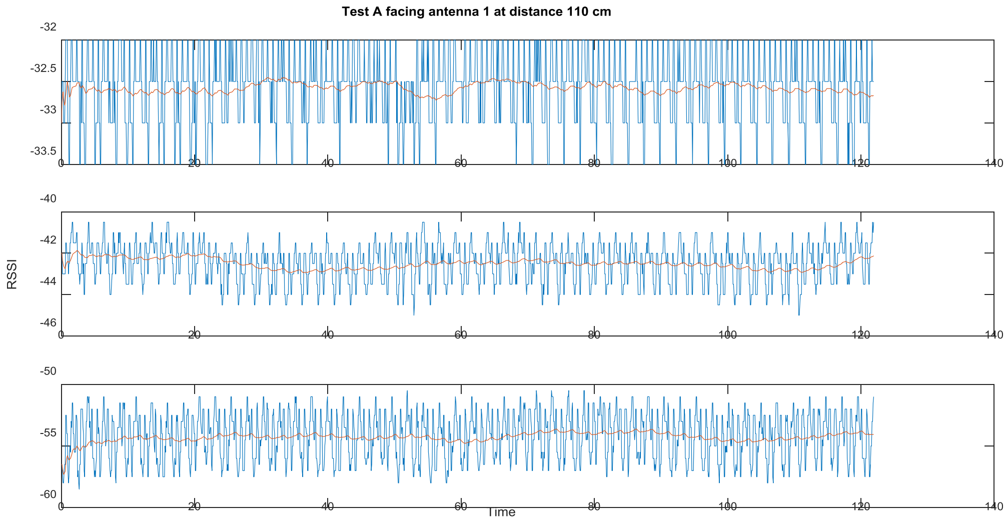

Figure A.23 tag A facing antenna 1 at distance 110 cm

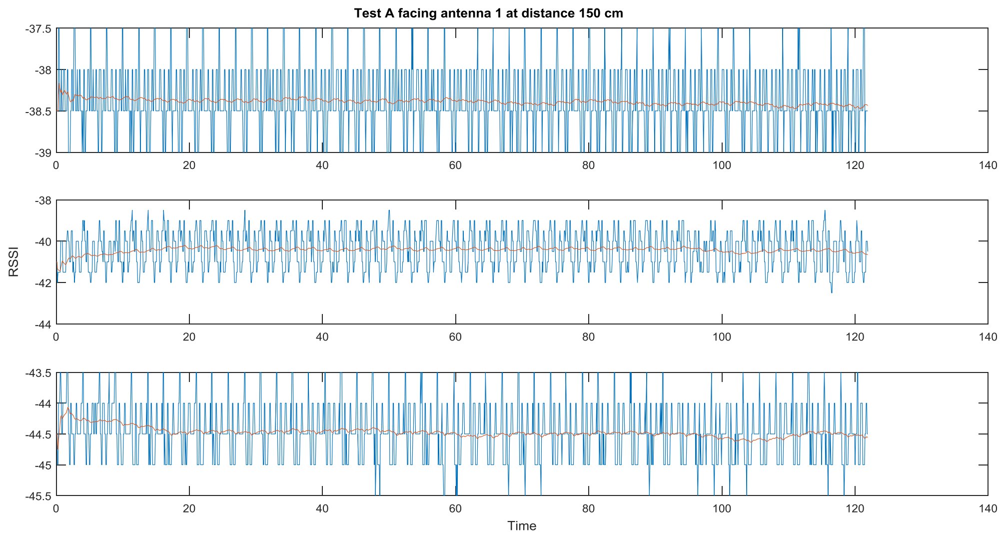

Figure A.24 tag A facing antenna 1 at distance 150 cm

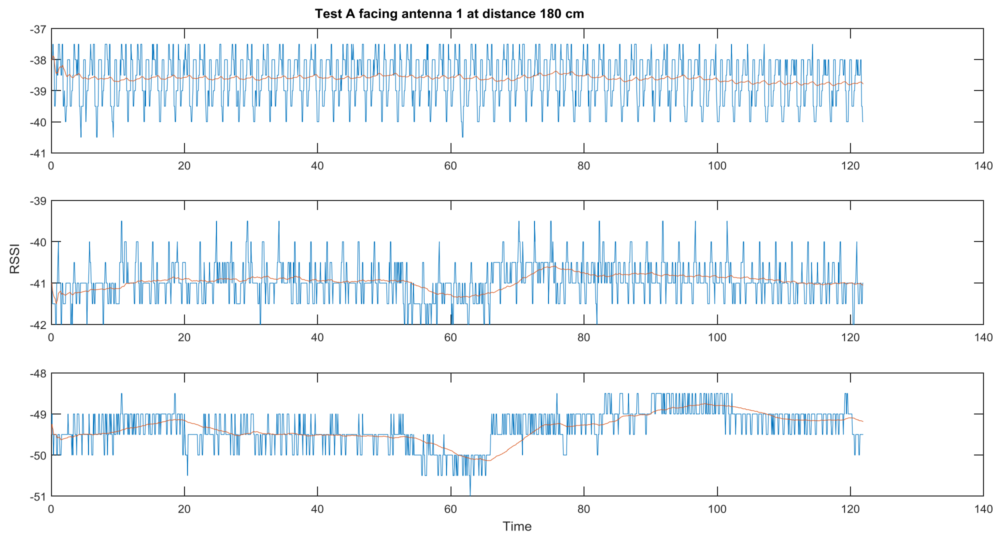

Figure A.25 tag A facing antenna 1 at distance 180 cm

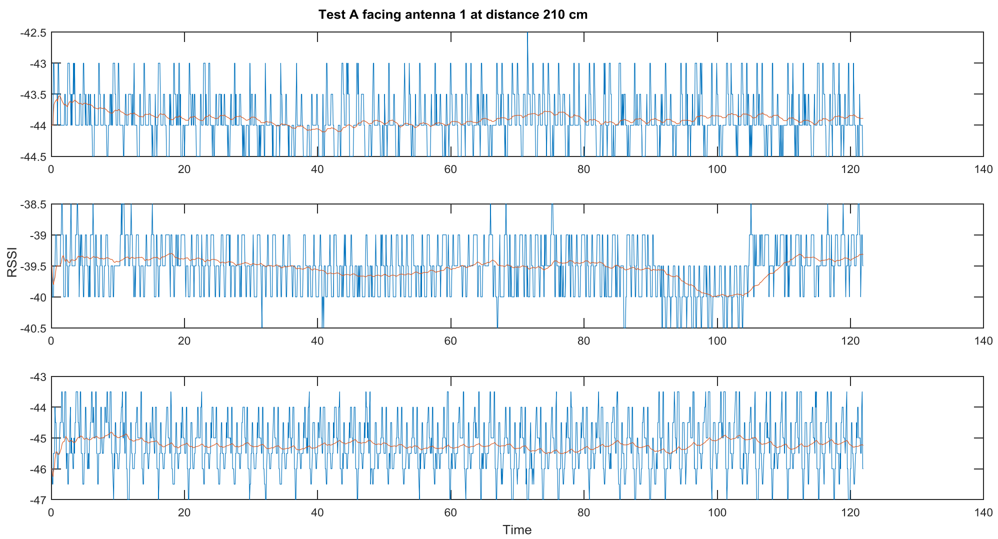

Figure A.26 tag A facing antenna 1 at distance 210 cm

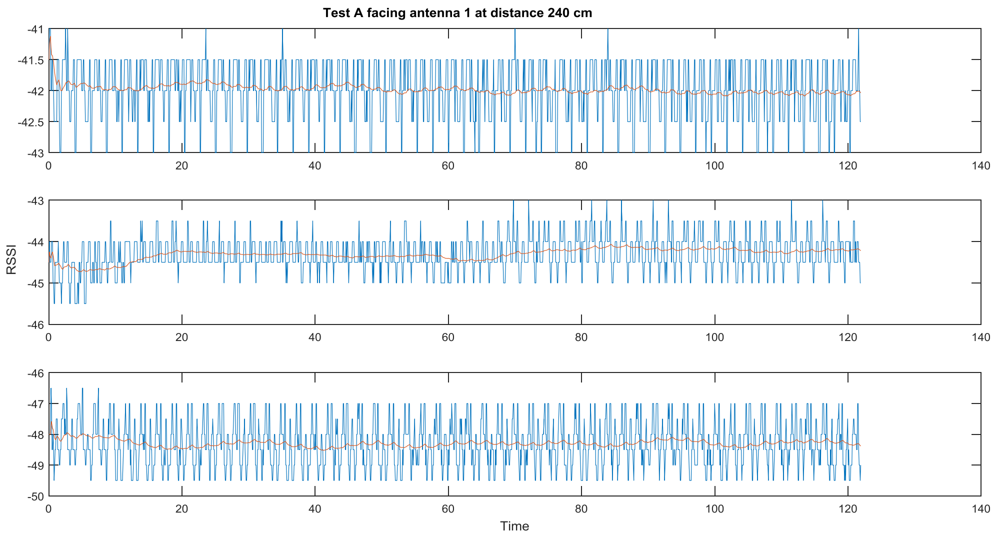

Figure A.27 tag A facing antenna 1 at distance 240 cm

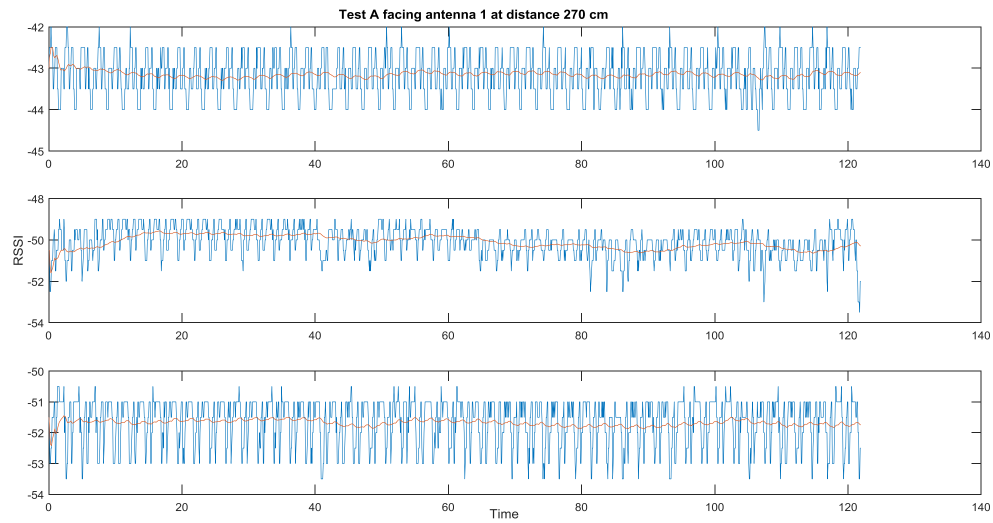

Figure A.28 tag A facing antenna 1 at distance 270 cm

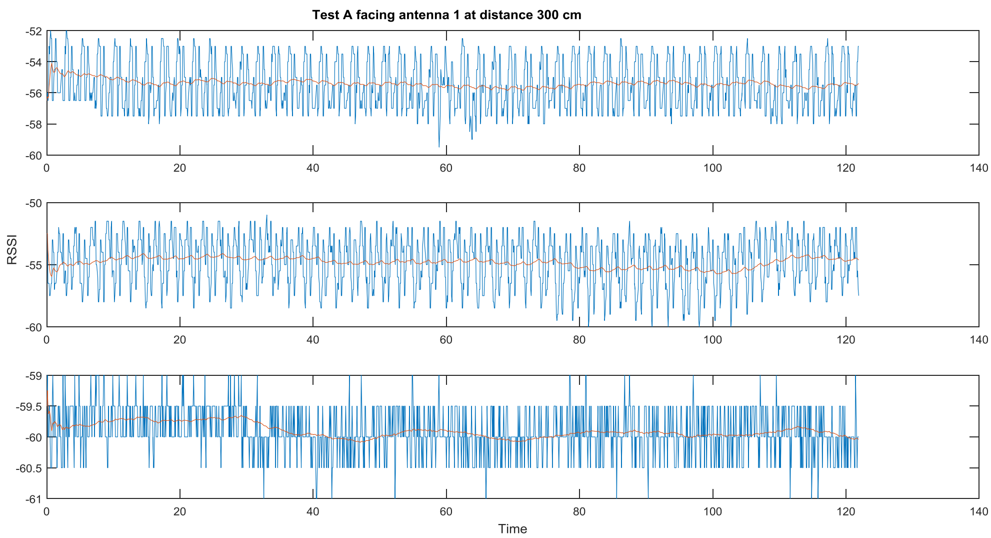

Figure A.29 tag A facing antenna 1 at distance 210 cm

6.4.2 Tag A facing antennas 2 and 3 experiment

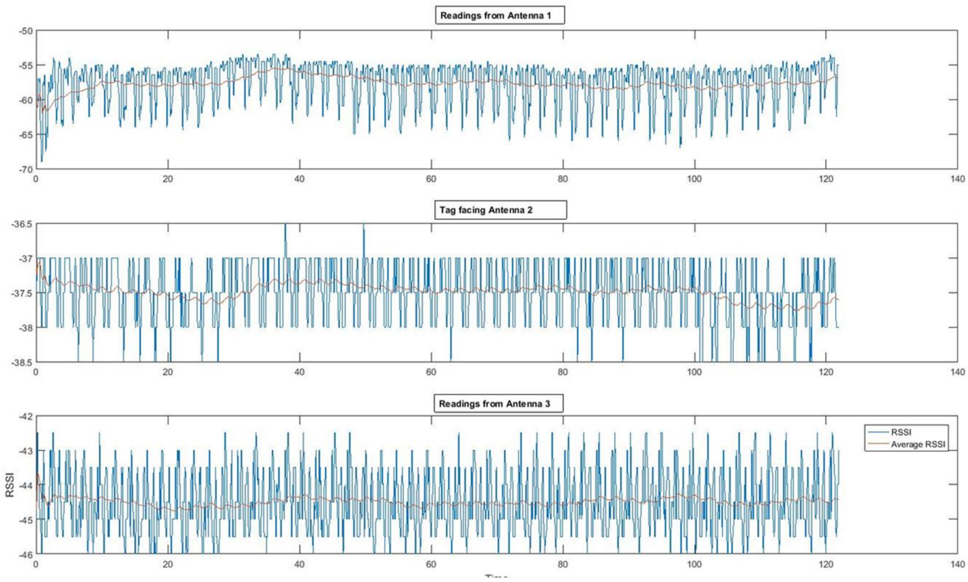

Figure A.30 Test A facing Antenna 2 at distance of 50

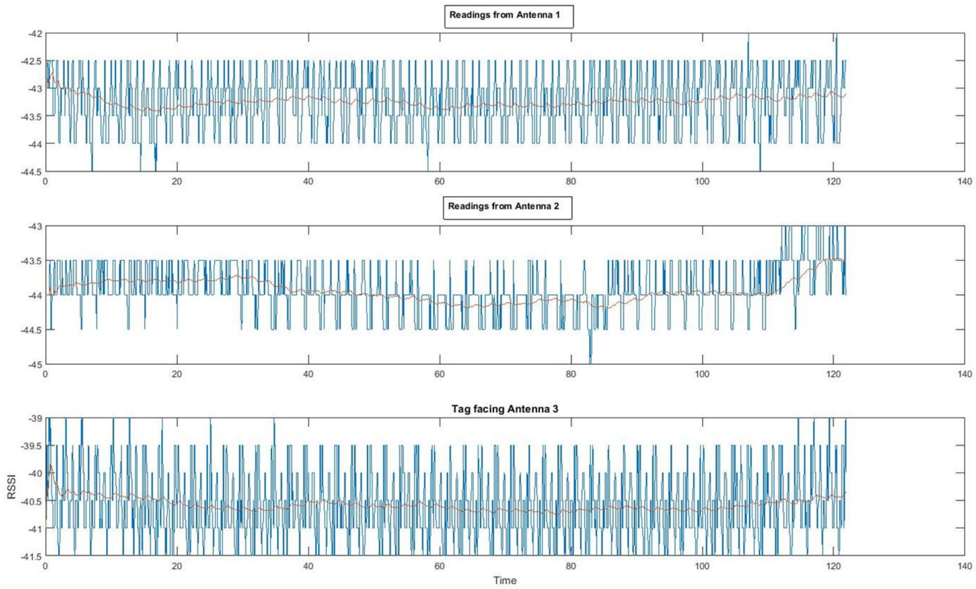

Figure A.31 Test A facing Antenna 3 at distance of 50

6.5 Neighbour tags Influence in Target Tag Experiment

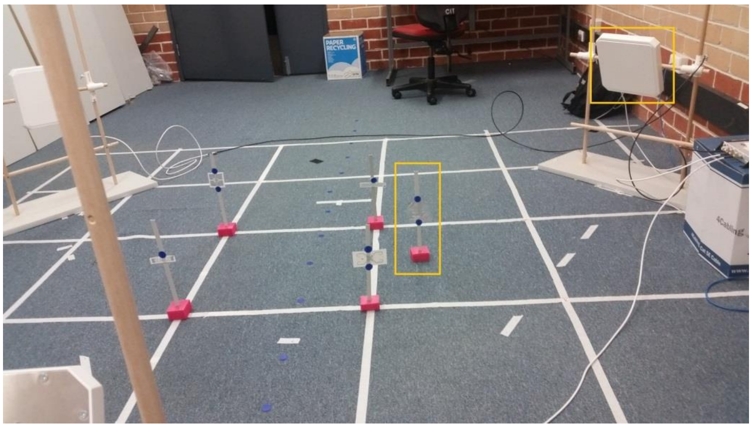

Figure A.32 Neighbouring tags test with target tag A facing Antenna 2

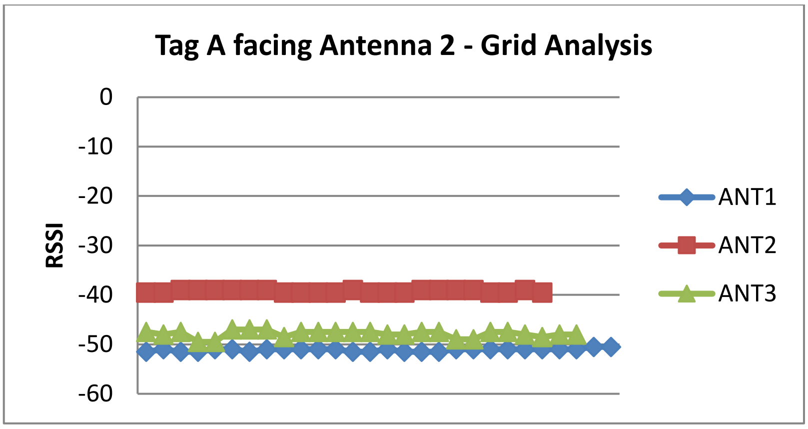

Figure A.33 tag A facing Antenna 2 – neighbouring tag analysis

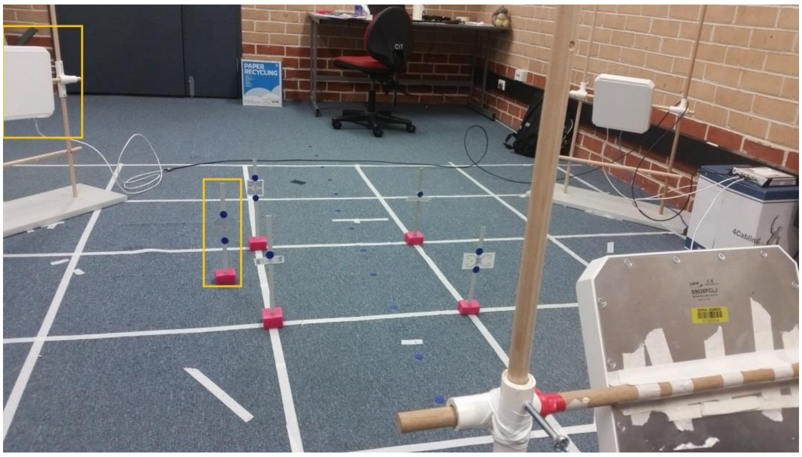

Figure A.34 Neighbouring tags test with target tag A facing Antenna 2

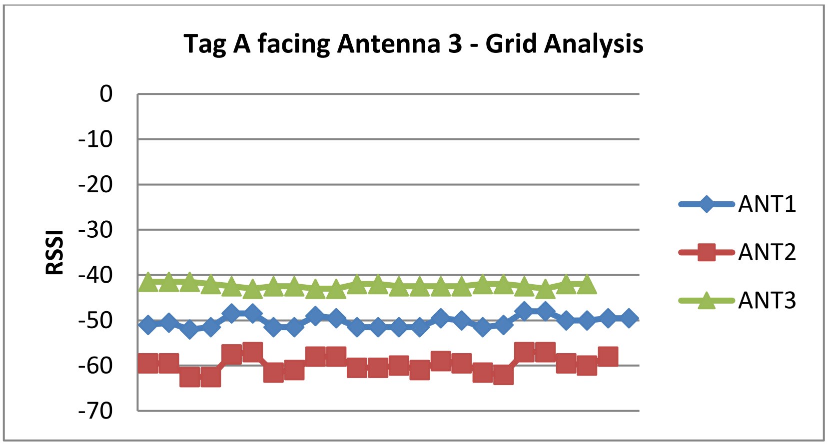

Figure A.35 tag A facing Antenna 3 – neighbouring tag analysis

Figure A.36 All passive RFID tags

B. APPENDIX B

Table B. 1 Real positions of tag A in coordinates in JAVA graphical user interface (JAVA GUI)vs. the estimated locations in stationary settings in JAVA GUI – trilateration experiments

Real Location – tag A CM		Estimated location – tag A CM		Δ d	% Accuracy
X	Y	X	Y		
180	360	349.2	477.3	205.9	77.12408
180	540	41.2	680.3	197.4	78.07152
180	720	1030.3	150.5	1023	13.7107
225	405	32.6	639	302.9	66.3398
225	495	317.2	514.4	94.22	89.53123
225	585	359	492.2	163	81.88928
270	270	349.3	444.9	192	78.66247
270	450	193.7	518.6	102.6	88.59952
270	630	151.8	590.4	124.7	86.14921
315	405	184.2	540.1	188	79.10619
315	495	58.6	700.5	328.6	63.49003
315	585	457	544.2	147.7	83.58387
360	360	224.8	520.1	209.5	76.71671

360	540	4	669.1	378.7	57.92382
360	720	435	410.5	318.5	64.61582
405	315	382	456.4	143.3	84.0824
405	405	418.4	460.3	56.9	93.67774
405	495	431.7	437.3	63.58	92.93576
405	585	465.8	434.7	162.1	81.98535
450	270	194.4	557.6	384.8	57.24819
450	450	463.5	441.9	15.74	98.25071
450	630	405.5	446.8	188.5	79.05254
495	315	460	459.8	149	83.44779
495	405	503.4	452.7	48.43	94.61845
495	495	478.4	435.8	61.48	93.16852
495	585	666.7	517.6	184.5	79.505
540	360	625.3	504.7	168	81.33658
540	540	489	440.4	111.9	87.56689
540	720	500.6	469.8	253.3	71.85742
585	315	617.1	484.5	172.5	80.83191
585	405	777.4	552	242.1	73.09671
585	495	715	532.2	135.2	84.97581

585	585	682.4	529.7	112	87.55513
585	675	604.3	482	194	78.4486
630	270	520.1	438.7	201.3	77.62892
630	450	671	510	72.67	91.9255
630	630	446	407	289.1	67.87659
675	405	561	460.5	126.8	85.91198
675	495	889.3	617.7	246.9	72.56213
675	585	909.7	611.7	236.2	73.75402
675	675	777.6	678.6	102.7	88.59298
720	360	1299.1	786.3	719.1	20.10126
720	540	762.6	541.3	42.62	95.26446

Table B. 2 Accuracy results (90%-100%) for tag A in real positions coordinates (JAVA GUI)vs. the estimated locations in stationary (JAVA GUI)- Multilateration experiments

Real Location – tag A CM		**Estimated Location – tag A CM**		**Δ d**	**% Accuracy**
X	Y	**X**	**Y**		
180	225	143	203	43.04649	**95.21706**
180	720	150	645	80.77747	**91.02473**
225	180	196	257	82.28001	**90.85778**
315	270	357	288	45.69464	**94.92282**
315	405	366	402	51.08816	**94.32354**
360	315	349	356	42.44997	**95.28334**
360	405	365	363	42.29657	**95.30038**
360	495	392	423	78.79086	**91.24546**
405	270	371	354	90.62009	**89.9311**
405	315	415	401	86.57944	**90.38006**
405	360	441	423	72.56032	**91.93774**
405	405	449	454	65.8559	**92.68268**
405	450	479	487	82.73452	**90.80728**
405	495	405	407	88	**90.22222**
405	540	480	491	89.58795	**90.04578**

450	360	441	443	83.48653	**90.72372**
450	405	440	432	28.79236	**96.80085**
450	450	485	475	43.01163	**95.22093**
450	495	503	447	71.50524	**92.05497**
450	540	493	482	72.20111	**91.97765**
495	450	430	426	69.28925	**92.30119**
495	495	495	496	1	**99.88889**
495	630	510	610	25	**97.22222**
540	405	483	435	64.41273	**92.84303**
540	450	540	515	65	**92.77778**
540	495	534	478	18.02776	**97.99692**
540	540	495	459	92.66067	**89.70437**
540	675	585	674	45.01111	**94.99877**
585	225	592	230	8.602325	**99.04419**
585	360	571	442	83.18654	**90.75705**
585	450	531	478	60.82763	**93.24137**
630	540	605	517	33.97058	**96.22549**
630	585	542	573	88.81441	**90.13173**
630	630	650	611	27.58623	**96.93486**

630	675	663	587	93.98404	**89.55733**
630	720	645	676	46.48656	**94.83483**
675	270	647	234	45.60702	**94.93255**
675	585	600	601	76.68768	**91.47915**
720	630	740	631	20.02498	**97.775**
720	720	701	694	32.20248	**96.42195**

Table B. 3 Accuracy results (80%-89%) for tag A in real positions coordinates in JAVA GUI vs. the estimated locations in stationary settings in JAVA GUI- Multilateration

Real Location – tag A CM		Estimated Location – tag A CM		Δ d	% Accuracy
X	Y	X	Y		
180	180	258	275	122.9187	86.34237
180	315	276	357	104.7855	88.35717
225	405	399	413	174.1838	80.64624
225	450	367	384	156.5886	82.60126
270	180	291	289	111.0045	87.66617
270	225	235	327	107.8378	88.01802
270	405	354	350	100.4042	88.84398
270	450	431	445	161.0776	82.10249
270	495	342	372	142.5237	84.16404
315	450	380	376	98.49365	89.05626
315	495	435	436	133.7199	85.14224
360	180	336	356	177.6288	80.26346
360	225	446	346	148.4486	83.50571
360	270	379	403	134.3503	85.07219
360	360	485	454	156.4001	82.62221

360	450	521	529	179.3377	80.07359
360	540	481	495	129.0969	85.6559
360	630	493	517	174.5222	80.60864
405	585	416	403	182.3321	79.74088
405	630	490	534	128.2225	85.75306
450	270	424	406	138.463	84.61522
450	315	439	422	107.5639	88.04845
450	585	550	555	104.4031	88.39966
450	630	501	505	135.0037	84.99959
450	675	593	603	160.1031	82.21077
495	225	437	386	171.1286	80.98571
495	270	506	443	173.3494	80.73896
495	315	525	463	151.0099	83.22112
495	360	538	504	150.2831	83.30188
495	405	537	531	132.8157	85.2427
495	540	400	512	99.0404	88.99551
495	585	605	610	112.8051	87.4661
495	675	550	552	134.7368	85.02925
540	270	609	339	97.58074	89.1577

540	315	568	454	141.7921	84.24532
540	360	435	420	120.9339	86.5629
540	720	593	563	165.7046	81.58838
585	315	590	426	111.1126	87.65416
585	495	594	657	162.2498	81.97224
585	585	514	505	106.9626	88.11527
585	630	731	735	179.836	80.01822
585	720	670	662	102.9029	88.56635
630	225	563	376	165.1969	81.64479
630	405	642	547	142.5061	84.16598
630	450	612	574	125.2996	86.07782
630	495	534	492	96.04686	89.32813
675	180	551	286	163.1318	81.87424
675	315	648	415	103.5809	88.49101
675	405	573	495	136.0294	84.88562
675	450	589	541	125.2078	86.08802
675	675	510	600	181.2457	79.86159
675	720	594	773	96.79876	89.24458
720	360	576	441	165.218	81.64244

720	495	614	554	121.3136	86.52071
720	540	686	683	146.9864	83.66818
720	585	593	489	159.2011	82.31099
720	675	866	750	164.1371	81.76254

Table B. 4 Accuracy results (70%-79%) for tag A in real positions coordinates in JAVA GUI vs. the estimated locations in stationary settings in JAVA GUI.

Real Location – tag A		**Estimated Location – tag A**			
CM		**CM**		**Δ d**	**% Accuracy**
X	**Y**	**X**	**Y**		
180	270	373	401	233.2595	74.08228
180	405	256	584	194.4659	78.39267
180	495	420	443	245.5687	72.71459
180	540	350	370	240.4163	73.28708
225	270	362	417	200.9428	77.67302
225	360	417	428	203.686	77.36822
225	495	418	428	204.2988	77.30013
225	585	349	358	258.66	71.26

270	270	435	432	231.2336	74.30737
270	315	425	453	207.5307	76.94103
270	540	345	332	221.1086	75.43238
270	585	430	454	206.7873	77.02363
270	675	510	567	263.1805	70.75772
315	180	417	384	228.0789	74.6579
315	225	271	418	197.952	78.00533
315	315	442	475	204.2768	77.30258
315	585	516	534	207.3692	76.95897
315	630	547	578	237.7562	73.58265
360	585	544	550	187.2992	79.18897
360	675	479	524	192.255	78.63833
405	180	398	401	221.1108	75.43213
405	225	446	425	204.1593	77.31564
405	675	623	654	219.0091	75.66565
405	720	567	586	210.238	76.64023
450	180	202	254	258.8049	71.24389
450	225	447	433	208.0216	76.88649
450	720	547	554	192.2628	78.63746

495	180	441	398	224.5885	75.04572
540	180	481	355	184.6781	79.48021
540	225	525	496	271.4148	69.8428
540	585	761	717	257.4199	71.39779
540	630	752	716	228.7794	74.58007
585	180	453	375	235.4761	73.83599
585	270	467	456	220.2726	75.52527
585	405	650	585	191.3766	78.73593
585	540	734	728	239.8854	73.34607
630	270	607	472	203.3052	77.41053
630	315	597	523	210.6015	76.59983
630	360	441	414	196.563	78.15967
675	225	520	447	270.7563	69.91596
675	360	521	474	191.6038	78.71069
675	540	751	767	239.3846	73.40171
675	630	478	477	249.4354	72.28496
720	225	622	406	205.8276	77.13027
720	270	576	400	194	78.44444
720	315	516	478	261.1226	70.98638

720	405	713	630	225.1089	74.9879
720	450	514	441	206.1965	77.08928
225	225	423	409	270.2961	69.9671

Table B. 5 Accuracy results below 70 for tag A in real positions coordinates in JAVA GUI vs. the estimated locations in stationary settings in JAVA GUI.

Real Location – tag A CM		**Estimated Location – tag A CM**		**Δ d**	**% Accuracy**
X	**Y**	**X**	**Y**		
		60%-70% Accuracy			
180	675	378	385	351.1467	60.9837
225	315	517	491	340.9399	62.11779
225	630	275	315	318.9436	64.56183
225	675	554	568	345.9624	61.55973
225	720	372	388	363.0881	59.65687
270	720	371	384	350.8518	61.01646
315	540	625	611	318.0267	64.6637
495	720	791	760	298.6905	66.81217
630	180	590	518	340.3586	62.18237
675	495	810	810	342.7098	61.92113

		50%-59% Accuracy			
180	**360**	**550**	**545**	**413.6726**	**54.03638**
180	**585**	**584**	**678**	**414.566**	**53.93711**
315	**360**	**619**	**683**	**443.5595**	**50.71561**
315	**720**	**688**	**702**	**373.4341**	**58.50733**
720	**180**	**627**	**552**	**383.4488**	**57.39458**
		Accuracy less than 50%			
180	450	598	805	548.4059	39.06601
180	630	703	710	529.0832	41.21298
225	540	960	980	856.6359	4.818238
270	360	980	974	938.6671	-4.29635
270	630	913	934	711.2419	20.97313
315	675	918	920	650.8717	27.68092
360	720	1036	1050	752.2473	16.41697
585	675	990	978	505.8004	43.79996